A Notebook on Probability, Statistics, and Data Science

To my family, friends and communities members who have been dedicating to the presentation of this notebook, and to all students, researchers and faculty members who might find this notebook helpful.

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Foreword

If software or e-books can be made completely open-source, why not a note-book?

This brings me back to the summer of 2009 when I started my third year as a high school student in Harbin No. 3 High School. In around the end of August when the results of Gaokao (National College Entrance Examination of China, annually held in July) are released, people from photocopy shops would start selling notebooks photocopies that they claim to be from the top scorers of the exam. Much curious as I was about what these notebooks look like, never have I expected myself to actually learn anything from them, mainly for the following three reasons.

First of all, some (in fact many) of these notebooks were more difficult to understand than the textbooks. I guess we cannot blame the top scorers for being so smart that they sometimes make things extremely brief or overwhelmingly complicated.

Secondly, why would I want to adapt to notebooks of others when I had my own notebooks which in my opinion should be just as good as theirs.

And lastly, as a student in the top-tier high school myself, I knew that the top scorers of the coming year would probably be a schoolmate or a classmate. Why would I want to pay that much money to a complete stranger in a photocopy shop for my friend's notebook, rather than requesting a copy from him or her directly?

However, things had changed after my becoming an undergraduate student in 2010. There were so many modules and materials to learn in a university, and as an unfortunate result, students were often distracted from digging deeply into a module (For those who were still able to do so, you have my highest respect). The situation became even worse as I started pursuing my Ph.D. in 2014. As I had to focus on specific research areas entirely, I could hardly split much time on other irrelevant but still important and interesting contents.

This motivated me to start reading and taking notebooks for selected books and articles, just to force myself to spent time learning new subjects out of my comfort zone. I used to take hand-written notebooks. My very first notebook was on *Numerical Analysis*, an entrance level module for engineering background graduate students. Till today I still have on my hand dozens of these notebooks. Eventually, one day it suddenly came to me: why not digitalize them, and make them accessible online and open-source, and let everyone read and edit it?

x Foreword

As most of the open-source software, this notebook (and it applies to the other notebooks in this series as well) does not come with any "warranty" of any kind, meaning that there is no guarantee for the statement and knowledge in this notebook to be absolutely correct as it is not peer reviewed. **Do NOT cite this notebook in your academic research paper or book!** Of course, if you find anything helpful with your research, please trace back to the origin of the citation and double confirm it yourself, then on top of that determine whether or not to use it in your research.

This notebook is suitable as:

- a quick reference guide;
- a brief introduction for beginners of the module;
- a "cheat sheet" for students to prepare for the exam (Don't bring it to the exam unless it is allowed by your lecturer!) or for lecturers to prepare the teaching materials.

This notebook is NOT suitable as:

- a direct research reference;
- a replacement to the textbook;

because as explained the notebook is NOT peer reviewed and it is meant to be simple and easy to read. It is not necessary brief, but all the tedious explanation and derivation, if any, shall be "fold into appendix" and a reader can easily skip those things without any interruption to the reading experience.

Although this notebook is open-source, the reference materials of this notebook, including textbooks, journal papers, conference proceedings, etc., may not be open-source. Very likely many of these reference materials are licensed or copyrighted. Please legitimately access these materials and properly use them.

Some of the figures in this notebook is drawn using Excalidraw, a very interesting tool for machine to emulate hand-writing. The Excalidraw project can be found in GitHub, *excalidraw/excalidraw*.

Preface

This notebook introduces probability and statistics, which is one of the fundamental undergraduate-level mathematics courses for science and engineering background students at a university.

In Part I of the notebook, probability theory is introduced. Probability theory studies how likely an event is to occur or not, and it offers rich models and tools to model and describe random values and stochastic events.

In Part II of the notebook, statistics is introduced. Statistics is a collection of methods to analyze and observe insights from data, verify statistics hypothesis and draw conclusions and predictions.

In Part III of the notebook, some of the most widely known and commonly used software solutions to statistics analysis and data science are introduced. Different from Parts I and II of the notebook that focus more on theory, Part III focuses more on using tools to solve practical problems. The widely used R language, Python, and MATLAB/Octive are introduced in Part III.

Key references of this notebook are summarized as follows.

- Spiegel, Murray, John Schiller, and Alu Srinivasan. *Probability and statistics*. 2020.
- Dekking, Frederik Michel, et al., A Modern Introduction to Probability and Statistics: Understanding why and how. Vol. 488. London: Springer, 2005.
- Kirill Eremenko, R Programming A-Z: R For Data Science With Real Exercises, Udemy Course.

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Part I Probability

Probability Basics

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This chapter introduces the basic concepts, axioms, theorems, and fundamental calculations of probability theory.

1.1 Sample Space, Event, and Probability

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1.2 Classic Probability

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1.3 Geometric Probability

"nobreak

1.4 Conditional Probability: A Glance at Bayes Theorem

 ${\rm ``nobreak'}$

1.5 Random Variable

Discrete

Continuous

1.6 Expectation, Variance, and More

Expectation

Median

Mode

Variance

Skewness

Kurtosis

Random Variables

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2.1 Discrete Random Variables and Distributions

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2.2 Continuous Random Variables and Distributions

"nobreak

2.3 Expectation, Variance, and More

 ${\rm ``nobreak}$

2.4 Special Distributions

[&]quot;nobreak

Joint Distributions

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3.1	Joint Probability Density Function	,
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3.1 Joint Probability Density Function

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3.2 Correlation

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3.3 Conditional Probability

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Part II Statistics

Sampling

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The data used for statistics analysis is usually a small portion collected from a huge group. The collected data is called a sample, and the huge group from which the sample is collected, the population. For example, the incomes of a random 1000 citizens as a sample may reflect the incomes of the entire city. Another example is that the working efficiency of a machine for the past months as a sample may reflect its working efficiency in its entire lifespan.

An important underlying assumption behind statistics is that the insights observed from the sample also apply to the population. With that regard, questions naturally come up. Why does this assumption hold? When does this assumption hold? In what extend does this assumption hold? What can be done to make the sample more effective and efficient when reflecting the population?

This chapter tries to answer the above questions. As it is introduced later, the inference from sample to population is not certain, as there is a chance (however small it might be) that the samples are completely biased from the population. Therefore, we must use probability in any statement drawn from statistics analysis.

4.1 Sampling Methods

When selecting elements from the population, make sure that all elements have a equal probability of being selected, hence, random sampling. Depending on how many times a member can be sampled, we have

- Sampling with replacement: a member can be chosen more than once.
- Sampling without replacement: a member can be chosen no more than once.

Sometimes it is interesting to compare the differences of the two methods, especially then the population is finite. An obvious difference is that by using sampling with replacement all the samples can be considered as "independent event", while by using sampling without replacement, previous samples may change the distributions in the remaining population, thus making the samples relevant. In this case, using sampling with replacement can theoretically be considered as sampling from an infinite population (by thinking that the population is duplicated as many times as necessary).

In practice, the population is usually so large, that sampling from a finite population can be considered as sampling from an infinite population, and the two methods would make no differences as far as it is concerned.

Consider the following examples. A set of N random variables are generated from a Gaussian distribution as the population. Sample the population M times using sampling with replacement and sampling without replacement, respectively. Calculate the sampled mean and variance after each sampling instance, and see how it converges to the mean and variance of the population.

In the first example, let N=100 and M=500. Figures 4.1 and 4.2 gives the cumulative mean and variance of sampling with and without replacement, respectively. The mean and variance are given by red and blue curves, respectively. The statistics obtained from the cumulative samples and from the population are given by the solid and dashed curves, respectively. Notice that in Fig. 4.2, after number of samples exceeding 100, the entire population has been sampled, and thus the sampling stops. This explains why its mean and variance stop fluctuating and converge to the population mean and variance, respectively.

In practice, however, the population size is often orders of magnitudes larger than the number of samples. In the second example, let N=10000 and M=500. The corresponding figures are given in Figs. 4.3 and 4.4. There is no obvious differences of the two figures from statistics perspective.

4.2 Model of Population

The features of the population is often not known, or at least not known entirely. It is possible to make some preliminary assumptions to the distribution of population, with parameters to be further confirmed using the samples.

For example, let X be a variable of the population. It could be, for example, the heights of all teenagers in a city. We can make an assumption that X follows some distribution f(x). A widely used assumption, in this scenario, is that f(x) is a Gaussian distribution with mean μ and standard deviation σ , and each element in the population, X_i , can be taken as a random variable generated from f(x). In the case of Gaussian distribution, since it is uniquely

Sampling 13

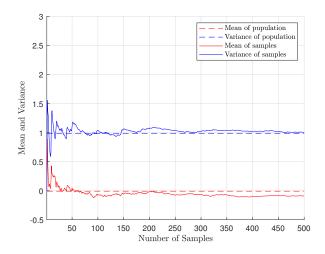


FIGURE 4.1 Sample with replacement, $N=100,\,M=500.$

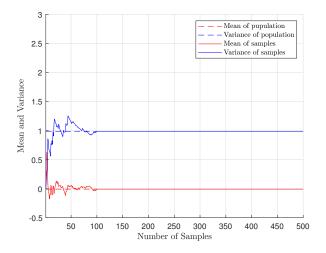


FIGURE 4.2 Sample without replacement, $N=100,\,M=500.$

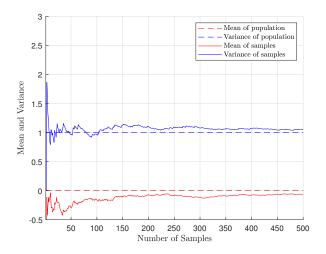


FIGURE 4.3 Sample with replacement, $N=10000,\,M=500.$

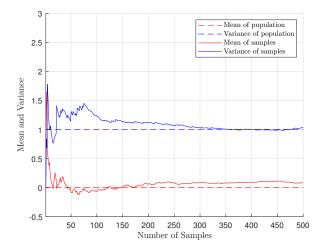


FIGURE 4.4 Sample without replacement, $N=10000,\,M=500.$

Sampling 15

characterized by μ and σ , other quantities such as the median, moments, skewness, etc., can be derived once μ and σ is calibrated.

The questions rise sequentially are:

- What are the parameters in the assumed distribution?
- Does it indeed follow the assumed distribution?

The answers to the above questions need to be found out via the samples, or more precisely, from the sample statistics.

4.3 Sample Statistics

Estimation

CONTENTS

Regression

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Part III Data Science Tools

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This chapter introduces R language basics, including the import (from files or databases), tidying, transformation, modeling, verification, and visualization of data. The use of R language in machine learning is also briefly covered.

Given that R is less popular than the more well-known and widely appreciated Python and MATLAB among engineering background researchers, this chapter serves as a basic introduction to R, before digging into its use in data science.

The first part of the chapter from Section 9.1 to Section 9.6 introduces

the basic grammar and visualization tools, and the second part of the chapter from Section 9.7 onwards more advanced practice of R.

9.1 R and RStudio Installation

R is a programming language for statistical computing and visualization. It is widely used among statisticians and data miners for developing statistical software and carrying out data analysis. R is free and can be downloaded from [1], where more details about R can also be found.

RStudio, also known as Posit, is an IDE widely used for R programming and testing. RStudio IDE is open-source and free of charge for personal use. It can be downloaded from [2].

Download R and RStudio from the aforementioned web sites, and install them sequentially.

9.2 R Packages Management

Before introducing the syntax, libraries, data frames and tools of R, it is worth introducing package management methods in R.

R packages, both built-in and third-party, provide power functions, data, and compiled codes for data analysis and visualization in a well-defined format. The packages can be published and shared online. CRAN is by far the most popular platform to store and share R packages.

To install or remove a package, use

```
install.packages("<package>")
remove.packages("<package>")
respectively. For example,
install.packages("pacman")
    To load a package, use
library(<package>)
for example
library(pacman)
```

After loading a package, the data frames and functions defined in that package can be used normally. Otherwise, to refer to a data frame or a function, the package name has to be used as a prefix as package>::<re>:<re>, which is inconvenient if the resource is used frequently.

```
To unload a package, use detach("package:<package>", unload = TRUE) for example detach("package:pacman", unload = TRUE)
```

The above methods work for both built-in packages (which often does not require installation) and third-party packages.

There are third-party packages that provides package management functions. The package pacman is an example of such package. With pacman installed and loaded, use the following commands to install, load and unload packages respectively.

```
p_install(<package>, ...) # install
p_load(<package>, ...) # install and load
p_unload(<package>, ...) # unload
p_unload(all) # unload all
```

An example of using pacman to load packages are given as follows.

```
pacman::p_load(
pacman, # package management
dplyr, # data manipulation
GGally, # data visualization
ggplot2, # data visualization
ggthemes, # data visualization
ggvis, # data visualization
httr, # url and http
lubridate, # date and time manipulation
plotly, # data visualization
rio, # io
rmarkdown, # documentation
shiny, # web apps development
stringr, # string operation
tidyr # data tidying
)
```

where notice that the above command can be executed before the loading of pacman itself, which is the reason pacman::p_load() prefix is used. These packages are commonly used in R projects. A brief explanation to them are given as comments following #. Notice that the first time installation of all the above packages may take a few minutes.

RStudio provides a graphical interface to manage packages as shown in Fig. 9.1.

Files	Plots	Packages	Help	Viewer	Presentation										
0	nstall (Update											Q,		
	Name			D	escription							Ve	ersion		
User	Library														4
	askpass			Sa	afe Password En	try for R,	Git, and SS	SH				1.	1	•	8
	asserttha	t		Ea	asy Pre and Post	Assertic	ns					0.	2.1	0	0
	base64er	nc		To	ools for base64	encoding)					0.	1-3	•	0
	bit			CI	lasses and Meth	ods for f	ast Memon	ry-Efficient E	Boolean Sel	ections		4.	0.5	•	0
	bit64			А	S3 Class for Ved	tors of 6	4bit Integer	ers				4.	0.5	•	0
	bslib			Ci	ustom 'Bootstra	p' 'Sass'	Themes for	'shiny' and	'rmarkdow	n'		0.	4.2	•	0
	cachem			C	ache R Objects v	with Auto	omatic Pruni	ning				1.	0.6	0	0
	cellrange	r		Tr	ranslate Spreads	heet Cel	l Ranges to	Rows and (Columns			1.	1.0	•	0
	cli			Н	elpers for Devel	oping Co	ommand Lin	ne Interface	s			3.	5.0	•	0
	clipr			Re	ead and Write fr	om the	System Clipb	board				0.	8.0	•	8
	colorspac	ce		Α	Toolbox for Ma	nipulatin	g and Asses	ssing Color	s and Palett	es		2.	0-3	•	⊗ (
	common	mark		Н	igh Performance	e Commo	onMark and	d Github Ma	rkdown Re	ndering in l	R	1.	8.1	•	0
	cpp11			Α	C++11 Interfac	e for R's	C Interface					0.	4.3	•	⊗ (
	crayon			C	olored Terminal	Output						1.	5.2	•	0
	crosstalk			In	nter-Widget Inte	ractivity	for HTML W	Vidgets				1.	2.0	•	0
	curl			Α	Modern and Fle	exible We	eb Client for	r R				4.	3.3	•	0
	data.table	e		Ex	xtension of `data	a.frame`						1.	14.6	•	0
	digest			Ci	reate Compact I	Hash Dig	ests of R Ob	bjects				0.	6.31	•	0
	dplyr			Α	Grammar of Da	ta Manip	oulation					1.	0.10	0	0
	ellipsis			To	ools for Working	with						0.	3.2	•	8
	evaluate			Pa	arsing and Evalu	ation To	ols that Prov	vide More [Details than	the Defaul	t	0.	19	0	0

FIGURE 9.1

Graphical interface to manage packages provided by RStudio.

9.3 R Programming Basics

This section introduces the basics of R programming, including the data types and syntax for basic R commands.

As the fundamentals, it is worth introducing here that R is case sensitive. Use # to lead a comment in R. Use print() to print a variable on the console. Typing the name of a variable often also prints it out, with a few exceptions such as when in a loop. Finally, use? followed by a function or a data frame name to check the help document for that function or data frame.

9.3.1 Data Types

R provides many data types. Commonly used data types are summarized in Table 9.1, where notice that <- is used to assign a value to a variable. Use typeof() to check the type of a variable. Alternatively, use is.numeric(), is.integer(), is.double(), is.character(), etc., to check whether a variable belongs to a particular data type.

Examples of assigning variables and checking their types are given as follows.

> n <- 2L

> typeof(n)

TABLE 9.1

Commonly used data types.

	Syntax (Example)	Description
integer	n <- 2L	An integer. Define an integer by a value
		followed by L.
double	x <- 2	An double float value.
complex	z <- 3+2i	A complex value.
character	a <- "a"	A character or a string.
logical	q <- T	A boolean value. Use T, TRUE and F,
		FALSE to represent true and false repec-
		tively.

```
[1] "integer"
> x <- 2
> typeof(x)
[1] "double"
> z <- 3+2i
> typeof(z)
[1] "complex"
> a <- "h"
> typeof(a)
[1] "character"
> q <- T
> typeof(q)
[1] "logical"
```

To transform data from one type to another, use as.<data-type>(). Examples of transforming data types are given as follows.

```
> n1 <- as.integer(2)
> typeof(n1)
[1] "integer"
> n2 <- as.integer("2")
> typeof(n2)
[1] "integer"
> x1 <- as.double(2L)
> typeof(x1)
[1] "double"
> x2 <- as.double("2")
> typeof(x2)
```

```
[1] "double"
> z1 <- as.complex("3+2i")
> typeof(z1)
[1] "complex"
> a1 <- as.character(2L)
> typeof(a1)
[1] "character"
> a2 <- as.character(2)
> typeof(a2)
[1] "character"
```

R supports arithmetic calculations of variables, including +, -, *, /, %/% (integer division), %% (modulus) and $\hat{}$ exponential. Examples of arithmetic calculations are given as follows.

```
> a <- 16
> b <- 3
> add <- a + b
> sub <- a - b
> multi <- a * b
> division <- a / b</pre>
> int_division <- a %/% b
> modulus <- a %% b
> exponent <- a ^ b
> add
[1] 19
> sub
[1] 13
> multi
[1] 48
> division
[1] 5.333333
> int_division
[1] 5
> modulus
[1] 1
> exponent
[1] 4096
```

R supports built-in and third-party functions which extend the capability of data manipulation. There is a rich set of functions for numerical calculations, string operations, probability density calculations and statistics analysis. Some of them are summarized in Tables 9.2, 9.3, 9.4, 9.5 and 9.6.

9.3.2 Conditionals and Loops

The if statement syntax is given as follows.

TABLE 9.2

3 T			
N 11	ımerical	calcu	lations

Syntax (Example)	Description
abs(x)	Absolute value.
sqrt(x)	Square root.
<pre>ceiling(x)</pre>	Smallest larger/equal integer.
floor(x)	Largest smaller/equal integer.
trunc(x)	Integer part of a variable.
round(x, n=0)	Round to n digit after decimal.
sin(x)	Trigonometric sin function.
cos(x)	Trigonometric cos function.
tan(x)	Trigonometric tan function.
log(x)	Natural logarithm.
log10(x)	Common logarithm.
exp(x)	Exponent.

TABLE 9.3

Logical comparisons.

nogream comparisons	•
Syntax (Example)	Description
х == у	Equal.
x != y	Not equal.
x > y, x < y	Greater than; less than.
x >= y, x <= y	Greater than or equal to; less than or equal to.
! x	Not.
х & у	And.
х І у	Or.
isTRUE(x)	Is true.

TABLE 9.4

String operations.

	ouring operations.	
Syntax (Example)		Description
	substr(s, n1, n2)	Segment of a string, from the n_1 -th charac-
		ter to n_2 -th character, both characters in-
		cluded.
	<pre>grep(p, s)</pre>	Searching of a pattern in a string.
	sub(s1, s2, s)	Find and replace patterns in a string.
	paste(s1, s2,, p="")	Concatenate strings with selected pattern to
		separate them.
	strsplit(s, p)	Split string into multiple strings at selected
		split points.
	tolower(s)	Convert to lower case.
	toupper(s)	Convert to upper case.

TABLE 9.5

Probability density related operations.

perations.
Description
Calculate the PDF of Gaussian distribution.
Calculate the CDF of Gaussian distribution.
Inverse function of pnorm().
Generate Gaussian distribution samples.
Calculate the probability of a binominal dis-
tribution.
Calculate the comulative probability of a bi-
nominal distribution.
Inverse function of pbinom().
Generate binominal distribution samples.
Calculate the probability of a Poisson distri-
bution.
Calculate the comulative probability of a Pois-
son distribution.
Inverse function of ppois().
Generate Poisson distribution samples.
Calculate the PDF of uniform distribution.
Calculate the CDF of uniform distribution.
Inverse function of punif().
Generate uniform distribution samples.

TABLE 9.6

Aggregate and statistics functions.

Syntax (Example)	Description
mean(1)	Mean.
sd(1)	Standard deviation.
median(1)	Median.
range(1)	Minimum and maximum.
min(1)	Minimum.
$\max(1)$	Maximum.
sum(1)	Sum

```
if(<condition>){
       <command>
} else if(<condition>){
        <command>
} else{
       <command>
}
An example of using if statement is givne below.
> x <- rnorm(1)
> if(x > 0){
       + y <- x
       + \} else if(x < 0){
       + y <- -x
       + } else{
          y <- 0
       + }
> print(x)
[1] -1.981445
> print(y)
[1] 1.981445
   The for loop syntax is given as follows.
for(<variable> in <vector>){
       <command>
}
where the <vector> can be a list of not only numbers but also characters.
Examples of using for loop are given below.
> for(i in 1:5){
             print(i)
       + }
[1] 1
[1] 2
[1] 3
[1] 4
[1] 5
> for(i in c("a", "b", "c")){
             print(i)
[1] "a"
[1] "b"
[1] "c"
   The while loop syntax is given as follows.
while(<condition>){
   <command>
}
```

An example of using while loop is given below.

```
> counter <- 0
> while(counter < 5){
+    print(counter)
+    counter <- counter + 1
+ }
[1] 0
[1] 1
[1] 2
[1] 3
[1] 4</pre>
```

An example of using the above to verify the law of the large number is given below.

9.3.3 User-Defined Functions

Define a simple function as follows. Note to run the codes where the function is described before calling the function.

9.3.4 Vectors

There are different types of vectors in R. The commonly used vector types include numeric vector (including both double and integer vector) and character vector. All elements in a vector must have the same data type. When different data type values are stored in a vector, they will be transferred to the most general data type. A single number or character is stored as a vector of length 1.

Notice that the index of a vector in R starts from 1 instead of 0. This is different with many other computer languages.

Use the following syntax to create a vector.

```
<vector> <- c(<value>, ...)
where <value> can be single element or a vector. For example,
> 1 <- c(1,2,3,4,5)
> print(1)
[1] 1 2 3 4 5
> typeof(1)
[1] "double"
```

Alternative ways to create a vector are given as follows. Use sequence to create a vector as follows.

```
<vector> <- seq(<from>, <to>, <by=1>)
<vector> <- <from>:<to> # equivalent to seq() with by=1
```

Use replica to create a vector as follows.

```
<vector> <- rep(<value>, <repeate>)
```

where <value> can be a numeric number, a character, or a vector. For example,

```
> 1 <- rep(c("a", "b", "cde"), 2)
> print(1)
[1] "a" "b" "cde" "a" "b" "cde"
```

Replica can also be used to create empty vector vy rep(NA, n).

A character vector can also be created by splitting strings using strsplit(). For example,

```
> a <- "Hello World!"
> b <- strsplit(a, "")
> print(b)
[[1]]
[1] "H" "e" "l" "l" "o" " " "W" "o" "r" "l" "d" "!"
```

To access the element in a vector, use <vector>[<index>]. Again, notice that the first element in a vector has the index of 1 instead of 0. The index can be an integer, or a list of integer such as a sequence. Examples are given below.

```
> s <- c("a", "b", "c", "d", "e", "f", "g")
> s[1]
[1] "a"
> s[7]
[1] "g"
> s[2:5]
[1] "b" "c" "d" "e"
> s[c(1L, 3L, 5L)] # s[c(1.1, 3.5, 5.9)] gives the same result; data
    type auto transferred
[1] "a" "c" "e"
```

Notice that accessing a single element in a vector is rarely used in practice, because most operations in R are done by the vector basis. Vectorization operation, also known as single-instruction-multiple-data operation, significantly speeds up the calculation in R, which is quite commonly seen in high-layer languages such as R and Python. This is due to the intepreting and wrapping techniques a high-layer language uses to communicate with the underlying low-layer languages, and also the support many processors have for parallel computing.

Most, if not all, of the numerical calculations, including +, -, *, /, %/%, %%, $^{\circ}$. Examples are given below.

```
> a <- c(1,2,3,4,5)
> b < -c(5,4,3,2,1)
> a + b
[1] 6 6 6 6 6
> a - b
[1] -4 -2 0 2 4
> a * b
[1] 5 8 9 8 5
> a / b
[1] 0.2 0.5 1.0 2.0 5.0
> a %/% b
[1] 0 0 1 2 5
> a %% b
[1] 1 2 0 0 0
> a ^ b
[1] 1 16 27 16 5
```

It is also possible to apply logic operations using vectors. Examples are given below.

```
> a <- c(1,2,3,4,5)
> b <- c(5,4,3,2,1)
> a < b
[1] TRUE TRUE FALSE FALSE FALSE
> a > b
[1] FALSE FALSE FALSE TRUE TRUE
> a == b
[1] FALSE FALSE TRUE FALSE FALSE
```

When the sizes of the vectors are not consistent, the shorter vector will repeat and populate to align with the longer vector. Examples are given below.

```
> a <- c(1,10)
> b <- c(1,2,3,4)
> a + b
[1] 2 12 4 14
> a - b
[1] 0 8 -2 6
> a * b
```

```
[1] 1 20 3 40
> a / b
[1] 1.0000000 5.0000000 0.3333333 2.5000000
> a %/% b
[1] 1 5 0 2
> a %% b
[1] 0 0 1 2
> a ^ b
[1] 1 100 1 10000
```

The vector can also play as the input argument or output return of a function, which can be difficult for some computer languages by nature. Again, a scalar is treated as a vector with length 1 in R.

An example of using the above to analyze the profit of a company is given below.

```
> revenue <- round(rnorm(12, 10000, 500), 2)
> expenses <- round(rnorm(12, 9500, 500), 2)
> # profit for each month
> profit.month <- revenue - expenses
> print(profit.month)
[1] -861.33 974.12 665.84 275.72 2374.99 1231.07 953.87 396.83 -536.62
    1202.72 529.28 522.62
> # profit after tax for each month (tax rate 30%)
> profit.month.aftertax <- 0.3*profit.month
> print(profit.month.aftertax)
[1] -258.399 292.236 199.752 82.716 712.497 369.321 286.161 119.049
    -160.986 360.816 158.784 156.786
> # profit margin for each month
> profit.month.margin <- round(100 * profit.month.aftertax / revenue,
> print(profit.month.margin)
[1] -2.85 2.69 1.97 0.84 6.88 3.40 2.99 1.16 -1.71 3.25 1.60 1.56
> # is good month
> profit.month.aftertax > mean(profit.month.aftertax)
[1] FALSE TRUE TRUE FALSE TRUE TRUE TRUE FALSE FALSE FALSE
> # is bad month
> profit.month.aftertax < mean(profit.month.aftertax)
[1] TRUE FALSE FALSE TRUE FALSE FALSE TRUE TRUE FALSE TRUE TRUE
> # is the best month
> profit.month.aftertax == max(profit.month.aftertax)
[1] FALSE FALSE FALSE FALSE TRUE FALSE FALSE FALSE FALSE FALSE
    FALSE
> # is the worst month
> profit.month.aftertax == min(profit.month.aftertax)
[1] TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
    FALSE
```

	L,13	[,2]	[5,1	L,4]	L,5]	L,6]
[1,]	E1,13					
[2,]						
[3,]			[3,3]			
[4,]						[4,6]

FIGURE 9.2

A demonstration of a matrix in R.

9.3.5 Matrices

A matrix in R is a recording of a table of data. Matrices are important because they are how data is often naturally organized, and they are also the build blocks of data frame in R.

A demonstration of a matrix in R is given by Fig. 9.2. Let the matrix be named A. The elements in the matrix can be accessed by the name of the table followed by the index coordinates. For example, in the figure, A[1,1] refers the first element and A[4,6] the last element.

It is possible to refer to an entire row or column. For example, use A[1,] to represent the first row of the matrix, by not specifying the column index. The same applies to the column.

Notice that all elements in a matrix must have the same data type.

A matrix can be created from scratch by stacking rows as follows. First, consider creating rows in the matrix. Then, use rbind() to bind rows. Finally, give names to each column and row.

```
# build rows
<row1> <- c(<value11>, ..., <value1n>)
...
<rowm> <- c(<valuem1>, ..., <valuemn>)
# build matrix
<matrix> <- rbind(<row1>, ..., <rowm>)
# (optional) clean rows
rm(<row1>, ..., <rowm>)
# give names
colnames(<matrix>) <- c("<column-name1>", ..., "<column-namen>")
rownames(<matrix>) <- c("<row-name1>", ..., "<row-namem>")
```

There are alternative ways, other than rbind(), to create a matrix. For example, matrix() convert a vector into a matrix. Similar with rbind(), cbind() binds the columns to form a matrix. Examples to create matrices using different methods are given below.

```
> A <- matrix(1:9, 3, 3)
> print(A)
[,1] [,2] [,3]
                  7
[1,]
        1
             4
        2
             5
                  8
[2,]
[3,]
        3
             6
> B \leftarrow rbind(c(1, 4, 7), c(2, 5, 8), c(3, 6, 9))
> print(B)
[,1] [,2] [,3]
                  7
[1,]
        1
             4
[2,]
        2
             5
                  8
[3,]
        3
> C \leftarrow cbind(c(1, 2, 3), c(4, 5, 6), c(7, 8, 9))
> print(C)
[,1] [,2] [,3]
                  7
[1,]
        1
             4
[2,]
        2
             5
                  8
[3,]
```

The name of the columns and rows can also be used to access an element, just by replacing the index with the name (with quotation mark) of the associated column or row. The same applies to vectors, as they can be treated as a one dimensional matrix. More details about naming a vector and columns and rows of a matrix are illustrated as follows.

To check the names relevant to a matrix, use names(<vector>), rownames(<matrix>) and colnames(<matrix>), depending on dealing with either a vector or a matrix. These commands can also be used to assign names. Examples are given below.

```
> v <- c(1, 2, 3, 4, 5)
> names(v) <- c("e1", "e2", "e3", "e4", "e5")
> print(v)
e1 e2 e3 e4 e5
1  2  3  4  5
> print(v[3])
e3
3
> print(v["e3"])
e3
3
> A <- matrix(1:9, 3, 3)
> colnames(A) <- c("col1", "col2", "col3")
> rownames(A) <- c("row1", "row2", "row3")
> print(A)
col1 col2 col3
```

```
row1
            4
                7
row2
           5
                8
       3
row3
            6
> print(A[2,2])
[1] 5
> print(A["row2", "col2"])
[1] 5
> print(A[2,])
col1 col2 col3
   5
       8
> print(A["row2",])
col1 col2 col3
    5
        8
> print(A[,2])
row1 row2 row3
   5 6
> print(A[,"col2"])
row1 row2 row3
    5
        6
```

To remove the names, simply assign NULL to the name.

Like the vector, operators are defined in matrix level as well. For example, for two matrices with the same shape, numerical operations such as +, -, *, /, %/%, %% and $\hat{}$ can be implemented.

R provides flexible and powerful data visualization tools, many of which more advanced than what is to be introduced in this section. This section introduces a simple matrix visualization function called matplot(), which plots the columns of a matrix against each other.

To demonstrate matplot(), consider the following example.

```
professor <- c(1130, 1026, 893, 922, 776)
student <- c(2, 14, 24, 49, 46)
citation <- rbind(professor, student)</pre>
colnames(citation) <- c("2018", "2019", "2020", "2021", "2022")
rownames(citation) <- c("Professor", "Student")</pre>
print(citation)
citation.ratio <- citation
citation.ratio["Professor",] <- round(citation["Professor",] / mean(</pre>
    citation["Professor",]) * 100, 1)
citation.ratio["Student",] <- round(citation["Student",] / mean(</pre>
    citation["Student",]) * 100, 1)
print(citation.ratio)
matplot(
       2018:2022, # x axis
       t(citation.ratio), # y axis
       type="b", # line and point selection
       pch = 15:16, # point shape
       col = 1:2, # color
       xlab = "Year",
```

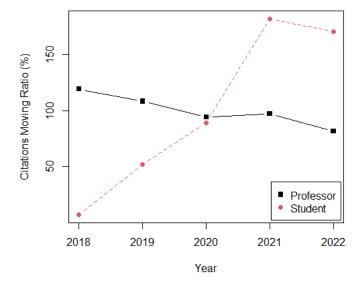


FIGURE 9.3

A demonstration of using matplot to plot trends.

```
ylab = "Citations Moving Ratio (%)"
)
legend("bottomright", inset = 0.01, legend = rownames(citation.ratio),
    pch = 15:16, col = 1:2, horiz = F)
```

where t() used inside matplot() calculates the transpose of a matrix. Save the above in a script and execute the code, to get the following Fig. 9.3.

Notice that matplot() is not widely used in particular in R.

As introduced earlier, a matrix or a vector can be split and segmented to form a smaller matrix or vector. It is worth mentioning that when a single column or row is selected, R will automatically treated the return as a vector instead of a matrix. An example is given below. When a matrix downgrades to a vector, the row name (if it has only one row), or the column name (if it has only one column) will be removed.

```
> A <- matrix(1:9, 3, 3)
> is.matrix(A)
[1] TRUE
> is.vector(A)
[1] FALSE
> is.matrix(A[1,])
[1] FALSE
> is.vector(A[1,])
[1] TRUE
```

To get consistent results, when segmenting matrix to get a single row or

plot

column vector, deliberately ask R to not drop the matrix dimensions. This can be done as follows. By doing this, the names assigned to columns and rows preserve.

```
> A <- matrix(1:9, 3, 3)
> is.matrix(A[1,,drop=F]) # select a row/column
[1] TRUE
> is.matrix(A[2,3,drop=F]) # select an element
[1] TRUE
```

An example of using the above to analyze the performance of players through a series of basketball games are given below.

```
# generate table
player_name <- c("player1", "player2", "player3")</pre>
match_name <- c("match1", "match2", "match3", "match4", "match5", "</pre>
    match6", "match7", "match8", "match9", "match10")
penalty_attempt <- abs(matrix(round(rnorm(3*10, 5, 2)), 3, 10))</pre>
penalty_point <- abs(penalty_attempt - matrix(abs(round(rnorm(3*10, 1,</pre>
    1))), 3, 10))
throw_attempt <- abs(matrix(round(rnorm(3*10, 15, 3)), 3, 10))</pre>
total_point <- abs(3*throw_attempt - abs(matrix(round(rnorm(3*10, 5, 1)
    ), 3, 10))) + penalty_point
rownames(penalty_attempt) <- player_name
colnames(penalty_attempt) <- match_name</pre>
rownames(penalty_point) <- player_name</pre>
colnames(penalty_point) <- match_name</pre>
rownames(throw_attempt) <- player_name</pre>
colnames(throw_attempt) <- match_name</pre>
rownames(total_point) <- player_name
colnames(total_point) <- match_name</pre>
# claim function
myplot <- function(table, xlab, ylab){
   row_name = rownames(table)
    column_name = colnames(table)
    matplot(
       1:length(column_name), # x axis
       t(table), # y axis
       type="b", # line and point selection
       pch = 1:length(row_name), # point shape
       col = 1:length(row_name), # color
       xlab = xlab,
       ylab = ylab
    legend("bottomleft", inset = 0.01, legend = row_name, pch = 1:
        length(row_name), col = 1:length(row_name), horiz = F)
}
```

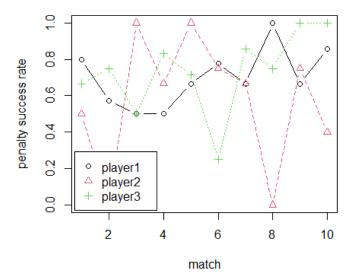


FIGURE 9.4 Plot of penalty success rate of the 3 players in 10 matches.

```
myplot(penalty_point / penalty_attempt, "match", "penalty success rate
    ") # penalty successful rate
myplot((total_point - penalty_point) / throw_attempt, "match", "average
    gained point per throw") # average point gained per throw
```

The results of the above codes are given in Figs. 9.4, 9.5.

9.4 Data Frames

Data frame, just like vector and matrix, is another data structure defined in R.

Both matrix and data frame use a table structure to store data, but data frame does not require all data to be with the same data type. Therefore, data frame is by nature the most closest format to represent a data structure from the real life. The aforementioned flexibility makes it maybe the most important and commonly used data structure in R.

In many applications and sample examples, data are stored and processed in data frame structure. When importing data from the real world, such as from a CSV file, the data is often read into a data frame before further processing.

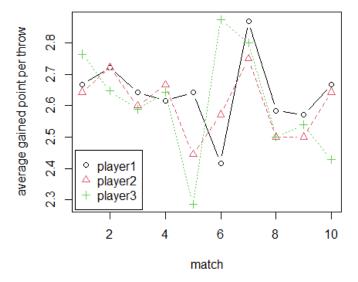


FIGURE 9.5
Plot of average point gained per throw attempt for the 3 players in 10 matches.

9.4.1 Data Import

One of the most common sources of data is CSV files. R provides convenient functions to read data from CSV files into data frames. Use the following commands to import data from a CSV file into a data frame.

The following command pops up a separate window that allows the user to choose a CSV file manually.

```
<data-frame> <- read.csv(file.choose()) # manual selection</pre>
```

The following commands import a specified CSV file.

```
setwd("<directory>") # navigate to the directory of the csv file
<data-frame> <- read.csv("<csv-file>.csv")
```

where notice that getwd() and setwd() are used to get and set current working directory, respectively.

9.4.2 Basic Operations

There are a few ways to access an element in a data frame. The methods used for accessing matrix element, including

```
<df>[<row-index>, <column-index>] <df>[<row-index>, "<column-name>"]
```

still work fine. Do notice that different from a matrix, the rows in a data frame

TABLE 9.7 Commonly used commands for data frame exploration.

Syntax (Example)	Description
nrow(df)	Number of rows.
<pre>ncol(df)</pre>	Number of columns.
head(df, n=6L)	Display the first few rows.
tail(df, n=6L)	Display the last few columns.
str(df)	A summary of the data frame, including the struc-
	ture of each column.
<pre>summary(df)</pre>	A summary of the data frame, including some of
	its statistics features.
<pre>levels(df\$<column>)</column></pre>	The level of the column.

have only indices but not names, while columns have both indices and names. In the case of data frame, \$ can be used to access a column as follows.

```
<df>$<column-name> # equivalent to <df>[, <column-name>]
```

which returns all elements in the column as a vector. The row index [<row-index>] can follow up to further specify an element if necessary.

Table 9.7 summarizes the commonly used commands for data frame exploration, such as checking its shape and data types.

An example of applying the above functions to iris data frame from the built-in datasets package is given below.

```
> library(datasets)
> nrow(iris)
[1] 150
> ncol(iris)
[1] 5
> head(iris)
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
          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
          5.4
6
                     3.9
                                  1.7
                                             0.4 setosa
> tail(iris)
    Sepal.Length Sepal.Width Petal.Length Petal.Width Species
145
            6.7
                       3.3
                                   5.7
                                               2.5 virginica
146
                       3.0
                                   5.2
                                               2.3 virginica
            6.7
147
            6.3
                       2.5
                                   5.0
                                               1.9 virginica
                                   5.2
148
            6.5
                       3.0
                                               2.0 virginica
149
            6.2
                       3.4
                                   5.4
                                               2.3 virginica
150
            5.9
                       3.0
                                    5.1
                                               1.8 virginica
> str(iris)
```

```
'data.frame': 150 obs. of 5 variables:
$ Sepal.Length: num 5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
$ Sepal.Width : num 3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
$ Petal.Length: num 1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
$ Petal.Width : num 0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
             : Factor w/ 3 levels "setosa", "versicolor", ...: 1 1 1 1 1
$ Species
     1 1 1 1 1 ...
> summary(iris)
 Sepal.Length
              Sepal.Width
                             Petal.Length Petal.Width
                                                              Species
Min. :4.300 Min. :2.000 Min. :1.000 Min.
                                                 :0.100
                                                                  :50
                                                         setosa
1st Qu.:5.100 1st Qu.:2.800 1st Qu.:1.600 1st Qu.:0.300 versicolor
     :50
Median: 5.800 Median: 3.000 Median: 4.350 Median: 1.300 virginica
     :50
Mean :5.843 Mean :3.057
                            Mean
                                  :3.758
                                           Mean
3rd Qu.:6.400 3rd Qu.:3.300 3rd Qu.:5.100 3rd Qu.:1.800
Max. :7.900 Max.
                    :4.400 Max. :6.900 Max.
> levels(iris$Species) # only works discrete-value columns
[1] "setosa"
              "versicolor" "virginica"
```

Data frame sub-setting works similarly with matrix. A sub-setting of multiple rows and columns of a data frame is a data frame. Notice that unlike the matrix case where if only one row is segmented the return is treated as a vector by default, in the case of a data frame the structure preserves. When a single column is segmented, however, in both matrix and data frame scenarios, the result will be treated as a vector by default, and <code>drop=F</code> can be used to preserve data frame structure.

An example is given below.

```
> library(datasets)
> print(iris[1:5,])
 Sepal.Length Sepal.Width Petal.Length Petal.Width Species
                     3.5
                                            0.2 setosa
          5.1
                                 1.4
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
> print(iris[1,])
 Sepal.Length Sepal.Width Petal.Length Petal.Width Species
          5.1
                     3.5
                                 1.4
                                            0.2 setosa
> is.data.frame(iris[1,])
> print(iris[,1]) # equivalent to print(iris@Sepal.Length)
  [1] 5.1 4.9 4.7 4.6 5.0 5.4 4.6 5.0 4.4 4.9 5.4 4.8 4.8 4.3 5.8 5.7
      5.4 5.1 5.7 5.1 5.4 5.1 4.6 5.1
 [25] 4.8 5.0 5.0 5.2 5.2 4.7 4.8 5.4 5.2 5.5 4.9 5.0 5.5 4.9 4.4 5.1
     5.0 4.5 4.4 5.0 5.1 4.8 5.1 4.6
 [49] 5.3 5.0 7.0 6.4 6.9 5.5 6.5 5.7 6.3 4.9 6.6 5.2 5.0 5.9 6.0 6.1
     5.6 6.7 5.6 5.8 6.2 5.6 5.9 6.1
```

```
[73] 6.3 6.1 6.4 6.6 6.8 6.7 6.0 5.7 5.5 5.5 5.8 6.0 5.4 6.0 6.7 6.3
      5.6 5.5 5.5 6.1 5.8 5.0 5.6 5.7
 [97] 5.7 6.2 5.1 5.7 6.3 5.8 7.1 6.3 6.5 7.6 4.9 7.3 6.7 7.2 6.5 6.4
      6.8 5.7 5.8 6.4 6.5 7.7 7.7 6.0
 [121] \  \, 6.9 \  \, 5.6 \  \, 7.7 \  \, 6.3 \  \, 6.7 \  \, 7.2 \  \, 6.2 \  \, 6.1 \  \, 6.4 \  \, 7.2 \  \, 7.4 \  \, 7.9 \  \, 6.4 \  \, 6.3 \  \, 6.1 \  \, 7.7 
     6.3 6.4 6.0 6.9 6.7 6.9 5.8 6.8
[145] 6.7 6.7 6.3 6.5 6.2 5.9
> is.data.frame(iris[,1])
[1] FALSE
> print(iris[,1,drop=F]) # preserve data frame
    Sepal.Length
              5.1
1
2
              4.9
3
              4.7
     # WRAPPED #
148
              6.5
149
              6.2
150
              5.9
> is.data.frame(iris[,1,drop=F])
[1] TRUE
```

To add a new column to an existing data frame, just assign values to a new column name as follows.

```
<df>$<new-column> <- <vector>
```

if there is a mismatch in size, <vector> will be cycled.

Ro remove a column, assign NULL to all the elements in that column as follows.

```
<df>$<column> <- NULL
```

9.4.3 Filtering

Filtering is about selecting specific rows from a data frame that meet specific criteria. A true-false vector can be used as a filter as follows.

```
<filter-name> <- <true-false-vector> # use true-false vector as filter <df>[filter,] # implement filter on data frame
```

An example is given below.

```
> library(datasets)
> filter <- iris$Sepal.Length >= 7
> print(iris[filter,])
   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
51
            7.0
                       3.2
                                   4.7
                                              1.4 versicolor
103
            7.1
                       3.0
                                   5.9
                                              2.1 virginica
106
            7.6
                       3.0
                                   6.6
                                              2.1 virginica
108
            7.3
                       2.9
                                   6.3
                                              1.8 virginica
110
            7.2
                       3.6
                                   6.1
                                              2.5 virginica
```

```
118
            7.7
                       3.8
                                   6.7
                                               2.2 virginica
119
            7.7
                       2.6
                                   6.9
                                               2.3 virginica
123
            7.7
                       2.8
                                   6.7
                                               2.0 virginica
126
            7.2
                       3.2
                                   6.0
                                               1.8 virginica
130
            7.2
                       3.0
                                   5.8
                                               1.6 virginica
131
            7.4
                       2.8
                                               1.9 virginica
                                   6.1
                       3.8
132
            7.9
                                   6.4
                                               2.0 virginica
136
            7.7
                       3.0
                                    6.1
                                               2.3 virginica
```

> filter <- iris\$Sepal.Length >= 7 & iris\$Sepal.Width >= 3.5
> print(iris[filter,])

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width Species
110	7.2	3.6	6.1	2.5 virginica
118	7.7	3.8	6.7	2.2 virginica
132	7.9	3.8	6.4	2.0 virginica

As shown above, it is possible to use &, | to form a more complex filter. The commands can be merged together as follows.

> print(iris[iris\$Sepal.Length >= 7,])

- 1		- + I 0	', -,			
	Sepal.Length	Sepal.Width	Petal.Length	Petal.W	idth Specie	es
51	7.0	3.2	4.7	1.4	versicolor	
103	7.1	3.0	5.9	2.1	virginica	
106	7.6	3.0	6.6	2.1	virginica	
108	7.3	2.9	6.3	1.8	virginica	
110	7.2	3.6	6.1	2.5	virginica	
118	7.7	3.8	6.7	2.2	virginica	
119	7.7	2.6	6.9	2.3	virginica	
123	7.7	2.8	6.7	2.0	virginica	
126	7.2	3.2	6.0	1.8	virginica	
130	7.2	3.0	5.8	1.6	virginica	
131	7.4	2.8	6.1	1.9	virginica	
132	7.9	3.8	6.4	2.0	virginica	
136	7.7	3.0	6.1	2.3	virginica	
	/· · г· ·	40 3 5			٦.	

> nrow(iris[iris\$Sepal.Length >= 7,]) # count the result number
[1] 13

9.4.4 Building Data Frames

To create a data frame from scratch, use function data.frame() as follows.

```
<df> <- data.frame(<vector>, ...) # add a column colnames(<df>) <- c("<column-name>", ...)

or
<df> <- data.frame(<column-name> = <vector>, ...)
```

An example is given below, where a data frame of mortgage price at 3 types of areas, namely "CBD", "city" and "suburbs", are is created. Arbitrary data is used.

```
# create data frame
vec_region <- c(rep("CBD", 100), rep("City", 100), rep("Suburbs", 100))</pre>
vec_size_cbd <- rnorm(100, 75, 10)</pre>
vec_size_city <- rnorm(100, 100, 15)</pre>
vec_size_suburbs <- rnorm(100, 150, 25)</pre>
vec_size = c(vec_size_cbd, vec_size_city, vec_size_suburbs)
vec_price_cbd <- vec_size_cbd*rnorm(100, 12500, 2500)</pre>
vec_price_city <- vec_size_city*rnorm(100, 7500, 1000)</pre>
vec_price_suburbs <- vec_size_suburbs*rnorm(100, 5000, 1000)</pre>
vec_price <- c(vec_price_cbd, vec_price_city, vec_price_suburbs)</pre>
mortgage_price <- data.frame(Region = vec_region, Size = vec_size,</pre>
    Price = vec_price)
rm(vec_region, vec_size_cbd, vec_size_city, vec_size_suburbs, vec_size,
      vec_price_cbd, vec_price_city, vec_price_suburbs, vec_price)
which gives the following result
> head(mortgage_price)
  Region
            Size
                     Price
     CBD 81.84889 1154873.0
1
     CBD 77.78946 831468.7
    CBD 84.60477 735265.2
     CBD 62.42625 829977.5
5
     CBD 65.42723 933851.3
     CBD 82.43867 1208589.0
```

A data frame can also be created from two existing data frames by merging them together. It works like the "JOIN" function in SQL, and in this sense it supports all "INNER JOIN", "LEFT JOIN", "RIGHT JOIN" and "OUTER JOIN". The syntax is given below.

In case the two data frames have duplicated columns other than the joining columns pair, use <df>\$<column> <- NULL to unnecessary columns.

9.5 Basic Data Visualizations Using qplot()

The package ggplot2 provides useful tools for visualization of a data frame. For example, both qplot() and ggplot() in ggplot2 provide plot function. Notice that in the late versions of ggplot2, qplot() is deprecated to encourage using of the more powerful ggplot(). With that been said, both functions are smart and flexible enough to produce many different types of plots.

An example of qplot() is given below, just to show some of its capability. Run the following codes, and Fig. 9.6 is displayed. It can be seen that qplot() is smart enough to automatically choose plot dype, background color, etc., to simplify the plot function.

```
library(datasets)
library(ggplot2)
qplot(
    data=iris,
    x=Sepal.Length*Sepal.Width,
    y=Petal.Length*Petal.Width,
    color=Species,
    size=I(3),
    xlab = "Sepal Area",
    ylab = "Petal Area"
)
```

As a recap, the mortgage_price data frame created previously can be visualized as follows. Figures 9.7 and 9.8 can be obtained.

```
library(ggplot2)
rm(list=ls())
# create data frame
vec_region <- rep(c("CBD", "City", "Suburbs"), each = 100)</pre>
vec_size_cbd <- rnorm(100, 75, 10)</pre>
vec_size_city <- rnorm(100, 100, 15)</pre>
vec_size_suburbs <- rnorm(100, 150, 25)</pre>
vec_size = c(vec_size_cbd, vec_size_city, vec_size_suburbs)
vec_price_cbd <- vec_size_cbd*rnorm(100, 12500, 2500)</pre>
vec_price_city <- vec_size_city*rnorm(100, 7500, 1000)</pre>
vec_price_suburbs <- vec_size_suburbs*rnorm(100, 5000, 1000)</pre>
vec_price <- c(vec_price_cbd, vec_price_city, vec_price_suburbs)</pre>
mortgage_price <- data.frame(Region = vec_region, Size = vec_size,</pre>
    Price = vec_price)
rm(vec_region, vec_size_cbd, vec_size_city, vec_size_suburbs, vec_size,
      vec_price_cbd, vec_price_city, vec_price_suburbs, vec_price)
mortgage_price$Price.Unit <- mortgage_price$Price / mortgage_price$Size</pre>
# plot
qplot(data=mortgage_price, x=Size, y=Price, color=Region, geom=c("point
     ", "smooth"))
```

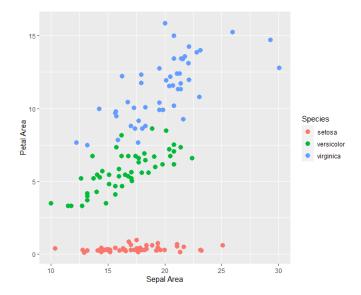


FIGURE 9.6 A demonstration of qplot.

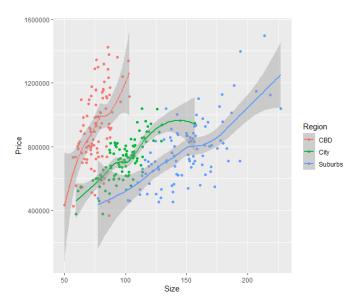
qplot(data=mortgage_price, x=Region, y=Price.Unit, geom="boxplot")

9.6 Advanced Data Visualizations Using ggplot()

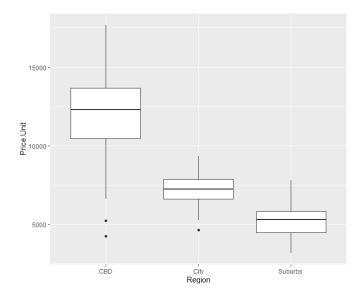
Function ggplot() is the main data visualization tool in ggolot2 package. It provides very flexible approaches for data plotting.

9.6.1 Grammar of Graphics

As proposed by Leland Wilkinson's Grammar of Graphics, a chart shall contain multiple independent and reusable layers including "data" (as data in data frames), "aesthetics" (how data maps to the chart, i.e., the logic of the plot; for example sample dots, curve, color block, or length of lines/bars), "geometries" (the actual color and shape of each element on the chart), "statistics" (information derived from the data being represented in the chart), "facets" (subplots of the same style align together for comparison), "coordinates" (the meaning and range of axis) and "theme" (overall design, such as title, label, etc.). A demonstrative Fig. 9.9 is given to illustrate the different layers in a chart.



 $\begin{tabular}{ll} FIGURE~9.7\\ A~demonstration~of~qplot~on~mortgage~price~data~frame. \end{tabular}$



 $\begin{tabular}{ll} {\bf FIGURE~9.8} \\ {\bf A~second~demonstration~of~qplot~on~mortgage~price~data~frame.} \\ \end{tabular}$

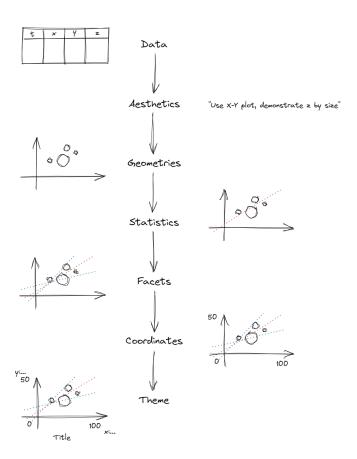


FIGURE 9.9 Multiple layers in chart design.

TABLE 9.8Commonly used commands for data frame exploration.

Geom	Description
<pre>geom_point()</pre>	Scatter plots and dot plots.
<pre>geom_line()</pre>	Line plots.
<pre>geom_bar()</pre>	Bar plots.
<pre>geom_histogram()</pre>	Histograms.
<pre>geom_boxplot()</pre>	Box plots.
<pre>geom_violin()</pre>	Violin plots.
<pre>geom_density()</pre>	Density plots.
<pre>geom_density2d()</pre>	2-dimensional Density plots.
<pre>geom_text()</pre>	Text Annotation.
<pre>geom_label()</pre>	Label on the observations.

9.6.2 Data, Aesthetics and Geometries Layers

Function ggplot() is a very good practice of implementing the above chart design and plotting philosophy. A simple example for ggplot(), just for quick demonstration purpose, is given below.

where aes() is used to build mappings in the aesthetics.

An interesting fact when using ggplot() is that, when adding a layer to the chat, the layer is literally added to ggplot(). In the program, this step by step build up an object, where ggplot() provides the most basic layers. Therefore, the above simple example is equivalent to

and the added layers are able to inherit the aesthetics settings, if it is not overwritten. And speaking of overwriting, even the x and y axis can be overwritten. The displaying name of the labels can be overwritten by stack xlab("") and ylab("") into the chart.

Function ggplot() provides many choices for geometries. The most commonly used ones are summarized in Table 9.8.

9.6.3 Statistics Layers

Similar to the case of geometries layers, statistics layers can also be stacked to ggplot(). As introduced earlier, statistics layers are often "add-on" layers that derives statistical features from the data and provide additional insights to the users.

Many functions in Table 9.8 are statistics layer built-in, such as geom_boxplot() which by nature is a statistics result presentation in the first place. Regression functions such as geom_smooth() also reveals statistical insights of the data. More details of these functions are as follows.

Consider using geom_boxplot() to visualize the mortgage_price data frame that was used in the previous section. Examples are given below.

```
library(ggplot2)
# create data frame
vec_region <- rep(c("CBD","City","Suburbs"), each = 100)</pre>
vec_size_cbd <- rnorm(100, 75, 10)</pre>
vec_size_city <- rnorm(100, 100, 15)</pre>
vec_size_suburbs <- rnorm(100, 150, 25)
vec_size = c(vec_size_cbd, vec_size_city, vec_size_suburbs)
vec_price_cbd <- vec_size_cbd*rnorm(100, 12500, 2500)</pre>
vec_price_city <- vec_size_city*rnorm(100, 7500, 1000)</pre>
vec_price_suburbs <- vec_size_suburbs*rnorm(100, 5000, 1000)</pre>
vec_price <- c(vec_price_cbd, vec_price_city, vec_price_suburbs)</pre>
mortgage_price <- data.frame(Region = vec_region, Size = vec_size,
    Price = vec_price)
rm(vec_region, vec_size_cbd, vec_size_city, vec_size_suburbs, vec_size,
     vec_price_cbd, vec_price_city, vec_price_suburbs, vec_price)
# processing
mortgage_price$Price.Unit <- mortgage_price$Price / mortgage_price$Size</pre>
# plot
p <- ggplot(data=mortgage_price, aes(x=Region, y=Price.Unit, color=
    Region)) + ggtitle("Mortgage uprice per area VS region") + xlab("
    Region") + ylab("Price per area")
p + geom_boxplot() + geom_jitter(aes(size=Size, color=Region), alpha
    =0.25)
```

and the result is shown in Fig. 9.10. Notice that ggtitle(), xlab(), ylab(), alpha are used in the plot. They are self-explanatory. A new geometry geom_jitter() is used, which works similarly with geom_point() except the additional vibration in the horizontal axis which makes the points clearer to see.

Function geom_smooth() is widely used for curve fitting. An example is given below.

```
library(ggplot2)
# generate data
t <- 1:500
var1 <- 1.5*t + rnorm(500, 0, 100)
var2 <- 0.5*t + rnorm(500, 200, 10) + t^1.3*rnorm(500, 0, 0.1)</pre>
```

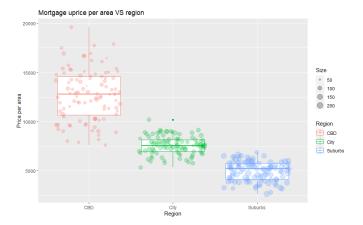


FIGURE 9.10

An example of box plot of the mortgage price data frame using ggplot() and geom_boxplot().

```
df <- data.frame(t=t, x=var1, y=var2)
# plot data
p <- ggplot(data=df) +
ggtitle("Plot of x and y VS t.") +
xlab("t") +
ylab("x and y") +
geom_point(aes(x=t, y=x), color="blue", shape=1, size=1.5) +
geom_smooth(aes(x=t, y=x), color="blue") +
geom_point(aes(x=t, y=y), color="red", shape=2, size=1.5) +
geom_smooth(aes(x=t, y=y), color="red")
p</pre>
```

Do note that aesthetics needs to be given to geom_smooth() in the above example. This is because aesthetics is not given in the base ggolot(). Notice that geom_smooth() can inherit aesthetics from the previous ggplot(), but not from the previous geom_point(). The plot is given by Fig. 9.11.

More functions similar to geom_smooth() are summarized in Table 9.9.

9.6.4 Facets Layers

The facets layer allows subplot of data. Consider the following example, where the distribution of mortgage price is studied using histogram. The following code can be used to plot the result in a single plot without the facets layer. The plot is given in Fig. 9.12.

```
library(ggplot2)
# create data frame
Region = rep(c("CBD","City","Suburbs"), each = 500)
```

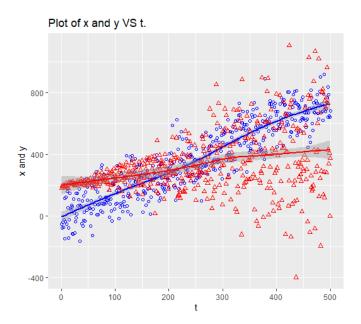


FIGURE 9.11 An example of using geom_smooth() for scatter point fitting.

TABLE 9.9
Functions that fit smooth lines to scatter points.

Function	Description
loess()	Non-parametric method for fitting a smooth line to a
smooth.spline()	scatter plot using locally weighted regression algorithm. Fits a smoothing spline to the data, which is a type of regression spline where the degree of smoothing is
	chosen automatically by cross-validation.
lm()	Linear Model, fits a linear relationship between inde-
	pendent and dependent variables by minimizing the residuals between the data points and the line.
glm()	Generalized Linear Model, similar to linear model, but
	it allows different distribution of error other than normal.
gam()	Generalized Additive Model, it is similar to GLM, but
	it allows non-parametric smooth functions to be added
	to the linear predictor.
<pre>geom_smooth()</pre>	A function in ggplot2 that is used to add a smooth line
	to a scatter plot, it uses method = "loess" by default
	but also allow to use other smoothing method like lm,
	gam etc.

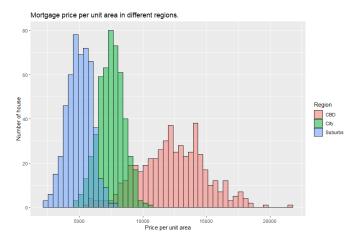


FIGURE 9.12

An example of histogram plot of house price per unit area in different regions in a single plot.

```
vec_size = list(vec_size_cbd = rnorm(500, 75, 10), vec_size_city =
    rnorm(500, 100, 15), vec_size_suburbs = rnorm(500, 150, 25))
vec_price = list(vec_price_cbd = vec_size$vec_size_cbd*rnorm(500,
    12500, 2500),
                vec_price_city = vec_size$vec_size_city*rnorm(500,
                    7500, 1000),
                vec_price_suburbs = vec_size$vec_size_suburbs*rnorm
                    (500, 5000, 1000))
mortgage_price <- data.frame(Region = Region,</pre>
                           Size = unlist(vec_size),
                           Price = unlist(vec_price))
mortgage_price$Region <- as.factor(mortgage_price$Region)</pre>
mortgage_price$Price.Unit <- mortgage_price$Price / mortgage_price$Size</pre>
# plot data
p <- ggplot(data=mortgage_price, aes(x=Price.Unit))</pre>
p + geom_histogram(aes(fill=Region), bins=50, color="black", alpha=0.5,
     position="identity") +
 ggtitle("Mortgage price per unit area in different regions.") +
  xlab("Price per unit area") +
 ylab("Number of house")
```

To use facets layer, revise the code as follows. Notice that facet_grid() is added to the plot, and its input <column>~. or .~<column> (it is okay to use <column1>~<column2> as well) decide the design of the subplots (how to arrange the rows and columns of the subplots).

```
library(ggplot2)
# create data frame
Region = rep(c("CBD","City","Suburbs"), each = 500)
```

```
vec_size = list(vec_size_cbd = rnorm(500, 75, 10),
                vec_size_city = rnorm(500, 100, 15),
                vec_size_suburbs = rnorm(500, 150, 25))
vec_price = list(vec_price_cbd = vec_size$vec_size_cbd*rnorm(500,
    12500, 2500),
                vec_price_city = vec_size$vec_size_city*rnorm(500,
                    7500, 1000),
                vec_price_suburbs = vec_size$vec_size_suburbs*rnorm
                    (500, 5000, 1000))
mortgage_price <- data.frame(Region = Region,</pre>
                           Size = unlist(vec_size),
                           Price = unlist(vec_price))
mortgage_price$Region <- as.factor(mortgage_price$Region)</pre>
mortgage_price$Price.Unit <- mortgage_price$Price / mortgage_price$Size</pre>
# plot data
p <- ggplot(data=mortgage_price, aes(x=Price.Unit))</pre>
p \leftarrow p + geom\_histogram(aes(fill=Region), bins=50, color="black", alpha
    =0.5, position="identity") +
  ggtitle("Mortgage price per unit area in different regions.") +
  xlab("Price per unit area") +
  ylab("Number of house")
p + facet_grid(Region~.) # put subplots for different regions in rows
p + facet_grid(.~Region) # put subplots for different regions in
    columns
```

The results are given in Figs. 9.13 and 9.14, depending on the subplot designs.

9.6.5 Coordinates Layers

Coordinate control is important. The coordinate layer allows setting limits to the axis and zooming in to the chart. An example of adding coordinates layers to a plot is given as follows. The same mortgage price data frame is used for illustration.

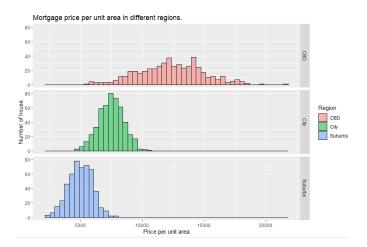


FIGURE 9.13

Use facets to plot the histogram of price per unit are of the house in different regions (subplots in rows).

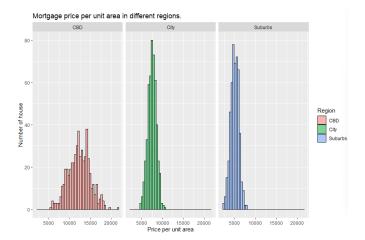


FIGURE 9.14

Use facets to plot the histogram of price per unit are of the house in different regions (subplots in columns).

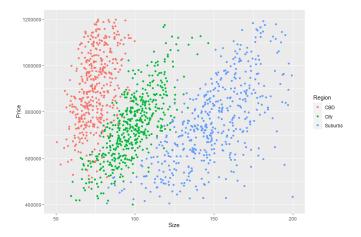


FIGURE 9.15

Add coordinates layer using xlim() and ylim().

where notice that two charts are generated. The first chart using xlim(), ylim removes all samples outside the boundary from the chart. While in the second chart using coord_cartesian(), all samples preserves and the chart zooms in towards the boundary. The results are given in Figs. 9.15 and 9.16, respectively. The difference can be observed near the boundary.

9.6.6 Themes Layers

Theme layers mainly refer to titles, labels, and other comments on the chart that help with understanding the content of the chart. As already demonstrated in previous examples, use xlab(), ylab() to add labels, ggtitle() to add title.

Use theme() to change the themes of the labels. An example is given below.

```
library(ggplot2)
# create data frame
Region = rep(c("CBD","City","Suburbs"), each = 500)
```

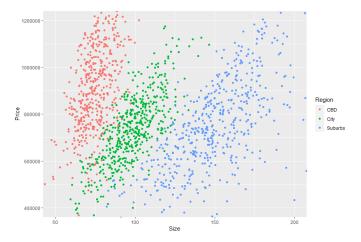


FIGURE 9.16

Add coordinates layer using coord_cartesian().

```
vec_size = list(vec_size_cbd = rnorm(500, 75, 10), vec_size_city =
    rnorm(500, 100, 15), vec_size_suburbs = rnorm(500, 150, 25))
vec_price = list(vec_price_cbd = vec_size$vec_size_cbd*rnorm(500,
    12500, 2500),
               vec_price_city = vec_size$vec_size_city*rnorm(500,
                    7500, 1000),
               vec_price_suburbs = vec_size$vec_size_suburbs*rnorm
                    (500, 5000, 1000))
mortgage_price <- data.frame(Region = Region,</pre>
                          Size = unlist(vec_size),
                          Price = unlist(vec_price))
mortgage_price$Region <- as.factor(mortgage_price$Region)</pre>
mortgage_price$Price.Unit <- mortgage_price$Price / mortgage_price$Size</pre>
# plot data
p <- ggplot(data=mortgage_price, aes(x=Price.Unit))</pre>
p <- p + geom_histogram(aes(fill=Region), bins=50, color="black", alpha
    =0.5, position="identity")
p + ggtitle("Mortgage price per unit area in different regions.") +
 xlab("Price per unit area") +
 ylab("Number of house") +
 theme(axis.title.x = element_text(color = "DarkGreen", size=15),
       axis.title.y = element_text(color = "DarkRed", size=15),
       axis.text.x = element_text(size=10),
       axis.text.y = element_text(size=10),
       legend.title = element_text(size=10),
       legend.text = element_text(size=8),
       legend.position = c(1,1), # right top corner of chart
       legend.justification = c(1,1), # legend align point
       plot.title = element_text(color = "DarkBlue", size = 15)
```



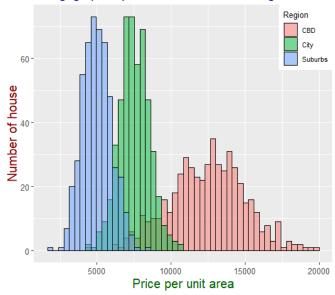


FIGURE 9.17

Mortgage price chart with theme.

)

The resulted chart is given in Fig. 9.17. Compare it with Fig. 9.12 to see the differences by applying theme() in the themes layer.

9.7 Data Preparation

"nobreak

9.7.1 Data Type Conversion

Data preparation including data tidy is one of the most tedious and time consuming parts when using R for data analysis. The section introduces useful techniques helpful with data preparation.

It is importnt that the data types of all the columns meet expectation, especially for numeric and factor (categorical) data types. Use str(<df>) to check the column data types of a data frame, and convert data types as follows.

<df>\$<column> <- factor(<df>\$<column>) # character/numeric to factor

```
<df>$<column> <- as.numeric(<df>$<column>) # character to numeric
<df>$<column> <- as.numeric(as.character(<df>$<column>)) # factor to
numeric
```

Notice that when converting factor type to other types, R may deal with the factor using the underlying "factorization integers" instead of the factor item names. An example is given below. It can be seen that the original 5.1, after being converted to factor then back to numeric, becomes 9. This is because the factorization integer for 5.1 is 9, as given by printing my_factor to the console.

```
> library(datasets)
> iris$Sepal.Length
  [1] 5.1 4.9 4.7 4.6 5.0 5.4 4.6 5.0 4.4 4.9 5.4 4.8 4.8 4.3 5.8 5.7
 [17] 5.4 5.1 5.7 5.1 5.4 5.1 4.6 5.1 4.8 5.0 5.0 5.2 5.2 4.7 4.8 5.4
 [33] 5.2 5.5 4.9 5.0 5.5 4.9 4.4 5.1 5.0 4.5 4.4 5.0 5.1 4.8 5.1 4.6
 [49] 5.3 5.0 7.0 6.4 6.9 5.5 6.5 5.7 6.3 4.9 6.6 5.2 5.0 5.9 6.0 6.1
 [65] 5.6 6.7 5.6 5.8 6.2 5.6 5.9 6.1 6.3 6.1 6.4 6.6 6.8 6.7 6.0 5.7
 [81] 5.5 5.5 5.8 6.0 5.4 6.0 6.7 6.3 5.6 5.5 5.5 6.1 5.8 5.0 5.6 5.7
 [97] 5.7 6.2 5.1 5.7 6.3 5.8 7.1 6.3 6.5 7.6 4.9 7.3 6.7 7.2 6.5 6.4
 [113] \  \  6.8 \  \, 5.7 \  \, 5.8 \  \, 6.4 \  \, 6.5 \  \, 7.7 \  \, 7.7 \  \, 6.0 \  \, 6.9 \  \, 5.6 \  \, 7.7 \  \, 6.3 \  \, 6.7 \  \, 7.2 \  \, 6.2 \  \, 6.1 
[129] 6.4 7.2 7.4 7.9 6.4 6.3 6.1 7.7 6.3 6.4 6.0 6.9 6.7 6.9 5.8 6.8
[145] 6.7 6.7 6.3 6.5 6.2 5.9
> my_factor <- factor(iris$Sepal.Length)</pre>
> my_numeric <- as.numeric(my_factor)</pre>
> my_numeric
  [1] 9 7 5 4 8 12 4 8 2 7 12 6 6 1 16 15 12 9 15 9 12 9
 [23] 4 9 6 8 8 10 10 5 6 12 10 13 7 8 13 7 2 9 8 3 2 8
 [45] 9 6 9 4 11 8 28 22 27 13 23 15 21 7 24 10 8 17 18 19 14 25
 [67] 14 16 20 14 17 19 21 19 22 24 26 25 18 15 13 13 16 18 12 18 25 21
 [89] 14 13 13 19 16 8 14 15 15 20 9 15 21 16 29 21 23 33 7 31 25 30
[111] 23 22 26 15 16 22 23 34 34 18 27 14 34 21 25 30 20 19 22 30 32 35
[133] 22 21 19 34 21 22 18 27 25 27 16 26 25 25 21 23 20 17
> typeof(my_factor)
[1] "integer"
> my_factor
  [1] 5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 5.4 4.8 4.8 4.3 5.8 5.7
 [17] 5.4 5.1 5.7 5.1 5.4 5.1 4.6 5.1 4.8 5 5 5.2 5.2 4.7 4.8 5.4
 [33] 5.2 5.5 4.9 5 5.5 4.9 4.4 5.1 5 4.5 4.4 5 5.1 4.8 5.1 4.6
 [49] 5.3 5 7 6.4 6.9 5.5 6.5 5.7 6.3 4.9 6.6 5.2 5 5.9 6 6.1
 [65] 5.6 6.7 5.6 5.8 6.2 5.6 5.9 6.1 6.3 6.1 6.4 6.6 6.8 6.7 6 5.7
 [81] 5.5 5.5 5.8 6 5.4 6 6.7 6.3 5.6 5.5 5.5 6.1 5.8 5 5.6 5.7
 [97] 5.7 6.2 5.1 5.7 6.3 5.8 7.1 6.3 6.5 7.6 4.9 7.3 6.7 7.2 6.5 6.4
[113] 6.8 5.7 5.8 6.4 6.5 7.7 7.7 6 6.9 5.6 7.7 6.3 6.7 7.2 6.2 6.1
[129] 6.4 7.2 7.4 7.9 6.4 6.3 6.1 7.7 6.3 6.4 6 6.9 6.7 6.9 5.8 6.8
[145] 6.7 6.7 6.3 6.5 6.2 5.9
35 Levels: 4.3 4.4 4.5 4.6 4.7 4.8 4.9 5 5.1 5.2 5.3 5.4 5.5 ... 7.9
```

When converting factor to other types, special caution is required. To

convert a factor to other types such as numeric, consider converting it to character first as given in the following example.

```
> my_numeric <- as.numeric(as.character(my_factor))
> my_numeric
[1] 5.1 4.9 4.7 4.6 5.0 5.4 4.6 5.0 4.4 4.9 5.4 4.8 4.8 4.3 5.8 5.7
[17] 5.4 5.1 5.7 5.1 5.4 5.1 4.6 5.1 4.8 5.0 5.0 5.2 5.2 4.7 4.8 5.4
[33] 5.2 5.5 4.9 5.0 5.5 4.9 4.4 5.1 5.0 4.5 4.4 5.0 5.1 4.8 5.1 4.6
[49] 5.3 5.0 7.0 6.4 6.9 5.5 6.5 5.7 6.3 4.9 6.6 5.2 5.0 5.9 6.0 6.1
[65] 5.6 6.7 5.6 5.8 6.2 5.6 5.9 6.1 6.3 6.1 6.4 6.6 6.8 6.7 6.0 5.7
[81] 5.5 5.5 5.8 6.0 5.4 6.0 6.7 6.3 5.6 5.5 5.5 6.1 5.8 5.0 5.6 5.7
[97] 5.7 6.2 5.1 5.7 6.3 5.8 7.1 6.3 6.5 7.6 4.9 7.3 6.7 7.2 6.5 6.4
[113] 6.8 5.7 5.8 6.4 6.5 7.7 7.7 6.0 6.9 5.6 7.7 6.3 6.7 7.2 6.2 6.1
[129] 6.4 7.2 7.4 7.9 6.4 6.3 6.1 7.7 6.3 6.4 6.0 6.9 6.7 6.9 5.8 6.8
[145] 6.7 6.7 6.3 6.5 6.2 5.9
```

where my_factor is generated previously.

It is possible for some columns in the data frame to look like a factor and a character string, but indeed should be handled as numeric values. For example, \$\$6,125.50 in many occasions should be treated just as 6125.0. These factor or character values cannot be converted to numeric values directly.

In such cases, consider using sub() or gsub() to replace patterns in a character, then convert it into numeric values. Notice that sub() replaces only the first encounter of the pattern, while gsub() replaces all the encounters. An example of using gsub() is given below.

```
> money_character <- c("S$6,273.15", "S$215.3", "S$8,987,756.00")
> typeof(money)
[1] "character"
> a <- gsub(",", "", money) # replace "," with ""
> a <- gsub("S\\$", "", a) # replace "S$" with ""
> money_numeric <- as.numeric(a)
> money_numeric
[1] 6273.15 215.30 8987756.00
> typeof(money_numeric)
[1] "double"
```

where notice that \$ is a special character defined in R, and to escape from that \\\$ is used. Notice that applying sub() and gsub() on a factor automatically converts it to character as a hidden step.

9.7.2 Handling Missing Data

There can be missing data in the data frame. There are a few ways to deal with missing data as follows.

- If the missing data can be derived from other columns, derive the missing data and fill in the blanks.
- If the missing data does not affect the rest analysis, leave it blank.

- Delete the row.
- Use interpolations to fill in the blank.
- Use correlations and similarities to fill in the blank.
- Argument a new column add a "data-missing" flag to that row.

If the missing data can be derived from other columns, derive the missing data and fill in the blanks.

In R, NA is a special variable used to indicate a missing value, and it is by itself of logical data type in addition to TURE and FALSE. Operations involving NA often return NA. Examples are given below.

```
> typeof(NA)
[1] "logical"
> TRUE == 1 # TRUE is equivalent with 1
[1] TRUE
> TRUE == 2
[1] FALSE
> FALSE == 0 # FALSE is equivalent with 0
[1] TRUE
> FALSE == -1
[1] FALSE
> TRUE == FALSE
[1] FALSE
> NA == NA
[1] NA
> NA == TRUE
[1] NA
> NA == FALSE
[1] NA
```

Use the following to filter for all rows with/without at least one NA.

```
<df>[complete.cases(<df>),] # all complete rows
<df>[!complete.cases(<df>),] # all incomplete rows
```

where complete.cases(<df>) returns a list made up of TRUE and FALSE indicating whether the associated row is complete or now.

Sometimes a blank string "" that we would expected to be treated as NA is not treated as so. To fix that, while importing the data frame (say, from a CSV file), use the following

```
df <- read.csv("<csv-name>", na.string=c("<pattern>", ...))
```

where "<pattern>" are the patterns in the original file to be replaced by NA, for instance, "", "ERROR", etc.

9.8 Connectivity with Data Sources

This section introduces the connectivity of R to the data sources, such as a file, or a database.

R for Data Science

Numpy and Scipy

CONTENTS

Python is has been increasingly popular for data science. Many libraries and tools have been developed delicately for Python to enhance its data analysis and visualization capability, such as numpy, scipy, scikit-learn, pandas, matplotlib tensorflow and pytorch, just to name a few.

This chapter introduces commonly used tools and approaches that data science adopt using Python. This part of the notebook is more application driven, and only the basic implementations are introduced. We are not digging into the theory supporting machine learning and artificial intelligence.

It has been increasingly popular today, to use Python together with Conda and jupyter notebook. Conda is an open-source language-agnostic package and environment management system. Jupyter notebook is an interactive computing platform for Python and other computer programming languages. The detailed introduction to the installation and usage of Conda and Jupyter notebook is not covered here. They are used when demonstrating the examples in this chapter.

${\bf 12}$

Pandas

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12.1 Introduction to pandas Package

The pandas package is a widely used powerful data processing toolkit. With pandas, Python gains the ability to handle data frames like Microsoft Excel. Some of the features and functions of pandas are worth introducing separately before hand, hence this section.

This is not to say that other packages are less important or less complicated by all means. Some of these packages work together with pandas to process data, while others may have their own ways to handle data frames. It is just that pandas is a fundamental package that can be introduced stand alone.

Assume that pandas is correctly installed in the machine, and a jupyter is opened as shown in Fig. 12.1.

12.2 Data Preprocessing

Preprocessing of data is always required in data science. The format of data needs to be tidied, and error samples removed. Even with very clean input data, it is often necessary to do feature analysis and scaling (feature normalization). For verification of the effectiveness of the model to be built, data splitting into training set and testing set is often required.

Commonly used packages are imported as follows.

import numpy as np



FIGURE 12.1

An example of a jupyter notebook.

import matplotlib.pyplot as plt
import pandas as pd

TensorFlow and PyTorch

Data Visualization in Python

MATLAB/Octave for Data Science

Bibliography

- [1] The r project for statistical computing.
- [2] Rstudio.