Assignment 1

Summary of Chapters 8–20

R for Data Science by Hadley Wickham, Rundel and Garrett Grolemund

Enock Mwanzia

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QUESTION 1

1. Write a very brief summary about
    a. The R programming language
    b. The installation of the programming language (half a page).

a) A Brief Summary of R programming language

R is a programming language and software environment for statistical analysis, graphics representation and reporting. It was created in 1993 by Ross Ihaka and Robert Gentleman at the University of Auckland, New Zealand, and is currently developed by the R Development Core Team since mid-1997. R is freely available under the GNU General Public License, and pre-compiled binary versions are provided for various operating systems like Linux, Windows and Mac. This programming language was named R, based on the first letter of first name of the two R authors (Robert Gentleman and Ross Ihaka), and partly a play on the name of the Bell Labs Language S.

The first stable release, Version 1.0.0, became available in February 2000. Since then, R has evolved significantly, supported by a rapidly growing community and an expansive ecosystem of packages. As of the writing of this paper, the latest version is R 4.5.2, released in November 2025.R as programming language has the following core features:

• It is a well-developed, simple and effective programming language which encompasses conditionals, loops, user defined recursive functions and input and output facilities.
• It has an effective and efficient data handling and storage facility.
• It provides a suite of operators for calculations on arrays, lists, vectors and matrices.
• It provides a large, coherent and integrated collection of tools for data analysis.

And it is used by companies such as Google, Microsoft, Facebook, X (Twitter), ANZ Bank, Ford, and New York Times in areas such as:

• Statistical Analysis – R programming provides inbuilt support for descriptive statistics, inferential statistics, regression analysis, time series analysis and classical statistical tests.
• Data Science – R is very important tool in data science workflow and supports data wrangling and preprocessing, data exploration and data import/export activities.
• Data Visualization – Using R, we can easily create static graphics, interactive visualizations, and maps.
• Machine Learning – R provides a rich environment for supervised learning, unsupervised learning, model evaluation, model selection and so on.
• Acedemia and Research – R is a preferred language in many premier academic and research institutions for teaching statistics and data science and to publish researches.

b) Installation of R programming language

R can be installed into different operating systems such Windows, Linux, and macOS as follows:

Windows Installation

To install R on Windows:

1. Download the installer (e.g. R-4.5.2 for Windows) from CRAN and save it to your local machine.
2. Double-click the .exe file to launch the installer.
3. On 64-bit Windows, the installer includes both 32-bit and 64-bit versions; the appropriate version will be installed automatically.
4. After installation, you can launch R from the Start Menu or by locating the executable (e.g., R\R-4.5.2\bin\Rgui.exe) in the Program Files directory. Opening R-GUI will display the R console where you can begin programming.

Linux Installation

Depending on the Linux distribution can be installed follows:

For RPM-based distributions (CentOS, Fedora, RHEL), you can install R using:

```
sudo yum install R
```

For Debian-based systems (Ubuntu), the equivalent command is:

```
sudo apt-get install r-base
```

QUESTION 2

2. Summarize the first **twenty** [**20**] chapters of the book discussed in class.

Introduction

The authors (Hadley Wickham &Garrett Grolemund) present R for Data Science (Wickham, Çetinkaya-Rundel, and Grolemund 2023) as a go-to resource for anyone aspiring to gain domain knowledge in data science field. While they acknowledge that no single book can make someone a "master" of R, they have carefully designed and covered the most important concepts and tools, encouraging readers to explore additional resources to reinforce their knowledge and achieve mastery.

They position R as a flexible and powerful programming language with vast ecosystem of statistical packages and advanced visualization tools. Combined with RStudio, its integrated development environment, R provides an ideal platform for managing the entire data science workflow efficiently and reproducibility. While acknowledging that other languages such as Python and Julia are equally valuable, the authors recommend focusing on mastering one tool at a time, since many skills are transferable across languages.

To get started, the book provides clear guidance on installing base R (which comes with built-in packages) and RStudio, the recommended IDE for interactive work. Additional packages can be installed as needed using install.packages(), and should always be loaded with library() before analysis.

The following sections summarize the key concepts from the first 20 chapters of the book.

Chapter 1: Data Visualization

The author begins his book by introducing data visualization concept; which is the graphical representation of information and data. Visuals are powerful as they convey important information to consumers more effectively than a piece of text alone. As the saying goes, a picture is worth a thousand words, this chapter leverages that idea by presenting tools that reveal patterns, relationships and trends in datasets.

R programming language offers extensive packages for creating visually appealing and informative plots. However, amongst those packages, ggplot2 package, which was engineered by co-author Hadley Wickham, stands out as the most versatile and widely adopted tool.

In this chapter, the author demonstrates how to use ggplot2 package with a few tweaks across colors(themes), aesthetic mappings, facets, geometric objects, statistical transformations, position adjustments and coordinate systems, to capture patterns, relationships and anomalies in datasets containing both categorical and numerical variables.

Chapter 2: Workflow: Basics

This chapter primarily focuses on the fundamental mechanics of writing and running code effectively in R and RStudio. The author reassures readers and practitioners that making errors while coding in R is inevitable. However, the solution is to keep practicing and work systematically.

The chapter covers arithmetic computations using R as a calculator, use of comments in code and creating objects using the assignment operator (<-), naming conventions especially the `snake case` for easier readability and consistency and finally calling functions by passing the requisite arguments between the parentheses ().

Chapter 3: Data transformation

In this chapter, the author introduces data transformation with dplyr package, a core member of tidyverse collection in R. Data transformation is a subset of data manipulation and entails making data organized, structured and usable for analysis, encompassing cleaning, selecting, filtering, reshaping, transforming and aggregation.

The author then deep dives into data manipulation using dplyr, introducing the following core verbs that can be piped (chained) together using the piping operator (%>%) from the magrittr package:

i. select() selects only the columns that you want, removing all others.
ii. filter() function helps us keep only the rows we need based on certain rules or conditions.
iii. arrange() function orders the table using a variable.
iv. mutate() function adds new columns or modifies existing ones in a dataset.
v. summarize() function reduces all rows into a one-row summary.
vi. group_by() function groups data by specific variables for subsequent operations.
vii. count() function in R is used to count the number of rows within each group of values, similar to a combination of the group_by() and summarize() functions.
viii. ungroup() remove grouping, and return to operations on ungrouped data.

Chapter 4: Workflow: Code Style

This chapter focuses on writing a clean, structured and acceptable code. As a programmer, your aim is not just writing a code that can run but to write a code that adheres to best programming practices. Just like any other programming language such as C with Betty and Python with pycodestyle as acceptable coding styles, R also has its own recommended style known as styler. This coding style can be installed via install.packages("styler") and be used RStudio command pallete.

Furthermore, this chapter goes on to emphasize importance of consistent naming conventions, the appropriate use of operators (including the piping operator, both in standard coding and data visualizations), and the use of structured comments for clear sectioning. All these elements contribute to production of clean and readable code that enhances maintainability and reusability.

Chapter 5: Data Tidying

This chapter focuses on tidying data using tidyr package which provides us with numerous tools for tidying up mess datasets. The authors propose that dataset(s) is considered tidy when:

Each variable is in its own column.
Each observation is in its own row.
Each value occupies a single cell.

Tidying datasets enhances consistency—uniform data reduces cognitive load and vectorization—ensures easier transformations since R naturally works well on column-wise operations.

Tidyr package which is a core member of tidyverse collection, provides the following tools that tidy data making visualization, transformation, and modeling become more intuitive and less error-prone:

a. pivot_longer(): It is used when information is stored in column names and it lengthens data by turning many columns into key-value pairs.
b. pivot_wider(): It is used when a single observation is stored across multiple rows and it widens data by creating more columns and reducing rows.

Chapter 6: Workflow: Projects

This chapter focuses on how a practitioner ought to organize his or her entire data analysis workflow so that the work is reproducible, shareable, and easy to revisit in the future. This chapter recommends considering your R scripts and data files as the true record of your work. By capturing all important computations in code, one can always recreate his or her results from scratch. To support this, RStudio should not be configured to save the workspace between sessions as it is prone to data loss. Preventing this destructive behaviour ensures one writes reproducible code and avoids future errors caused by hidden objects in memory.

The chapter also introduces the concept of the working directory which is basically a folder where R looks for input files and saves outputs. Rather than using absolute paths or manually setting the directory inside R, it is best practice is to keep each analysis in its own dedicated folder and work with relative paths instead.

Finally, the author presents RStudio Projects as the professional way to manage analyses. RStudio project keeps all files related to an analysis including scripts, data, plots, and results in one place. Opening the project restores your working directory and file layout, giving one a clean and familiar workspace every time. This makes it easier to reproduce, collaborate on, and maintain over time.

Chapter 7: Data Import

In this chapter, the authors focus on import data (flat files) into R environment using readr package which is core member of tidyverse. Flat files are loaded into R environment using read_csv(), read_tsv(), read_delim() as follows:

```
variable_name1 <- read_csv("filename.csv") variable_name2 <- read_tsv("filename.txt") variab
```

Readr package also provides the functions to facilitate data exploration on column types:

- col_logical() and col_double() read logicals and real numbers.
- col_integer() reads integers.
- col_character() reads strings.
- col_factor(), col_date(), and col_datetime() create factors, dates, and datetimes.
- col_number() is a permissive numeric parser that will ignore non-numeric components.
- col_skip() skips a column so it's not included in the result.

Readr also provides write capabilities allowing us to write to files using the following functions: write_csv, write_tsv and write_rds.

Chapter 8: Workflow: Getting Help

This chapter addresses a critical but often underestimated aspect of data science: *how to learn effectively and solve problems independently.* Rather than focusing on syntax or functions, this chapter emphasizes mindset, habits, and professional development.

The authors highlight that *most real-world data science time is spent debugging, researching, and refining*, not writing new code from scratch. Consequently, learning how to ask good questions and seek help efficiently becomes a core technical skill.

A central idea is the use of *targeted searching. This* significantly improves the relevance of results and leads users to authoritative sources such as official documentation, Stack Overflow, GitHub issues and community forums.

Additionally, the authors introduce the concept of a *reprex (reproducible example).* A reprex is a minimal, self-contained piece of code that demonstrates a problem clearly. Reprex enhances clarity of thought, reduces ambiguity, and increases the likelihood of receiving helpful answers from others.

Example

```r
library(reprex)

x <- c(3, 2, 7, 4)
mean(x)
```

```
[1] 4
```

Chapter 9: Layers

This chapter deepens understanding of ggplot2 by introducing the layered grammar of graphics, which underpins all ggplot visualizations. The chapter explains that every plot is constructed by stacking layers, each responsible for a specific aspect of the visualization.

The authors explain how *aesthetic mappings* link variables in a dataset to visual properties such as position, color, size, and shape. These mappings can be global (applied to all layers) or local (applied to specific geoms), giving the practitioner precise control over plot behavior.

The chapter then explores *geometric objects (geoms),* which define how data are represented visually (points, lines, bars, boxplots, etc.). This abstraction allows the same data to be viewed from multiple perspectives by changing the geom rather than the dataset itself. This is facilitated by:

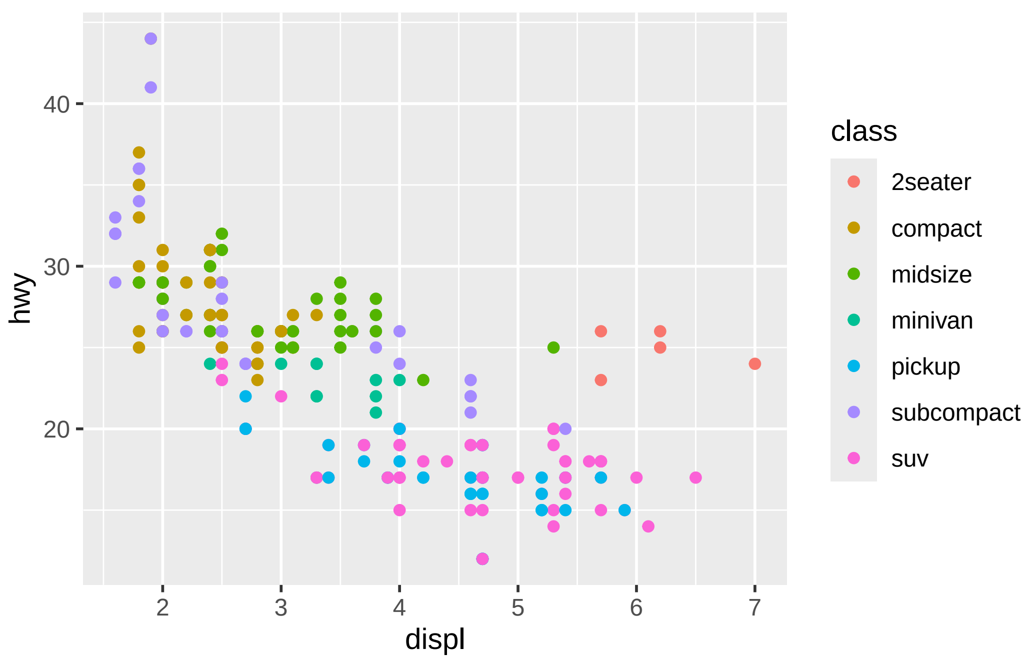
- **Facets**, which split data into subplots for comparison,
- **Statistical transformations**, which summarize or model data before plotting,
- **Positional adjustments,** which affects how the data is positioned.
- **Coordinate systems**, which affect how data are projected onto the plotting space.

Example 1

```r
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.6
v forcats   1.0.1     v stringr   1.6.0
v ggplot2   4.0.1     v tibble    3.3.0
v lubridate 1.9.4     v tidyr     1.3.1
v purrr     1.2.0
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x purrr::%||%()   masks base::%||%()
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becon
```

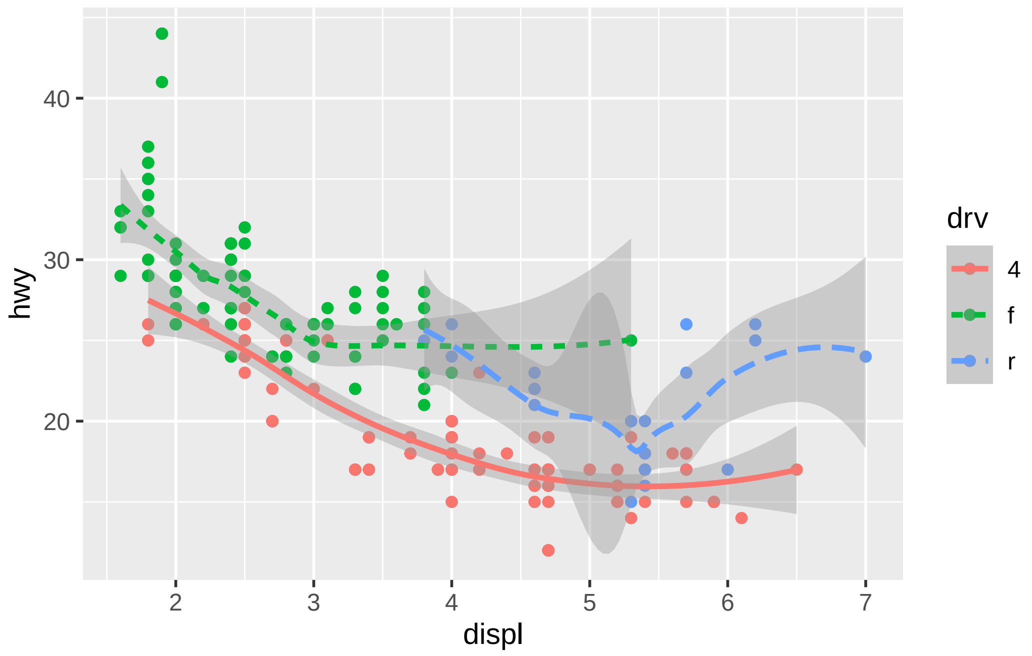
```r
ggplot(mpg, aes(x = displ, y = hwy, color = class)) +
  geom_point()
```



Example 2

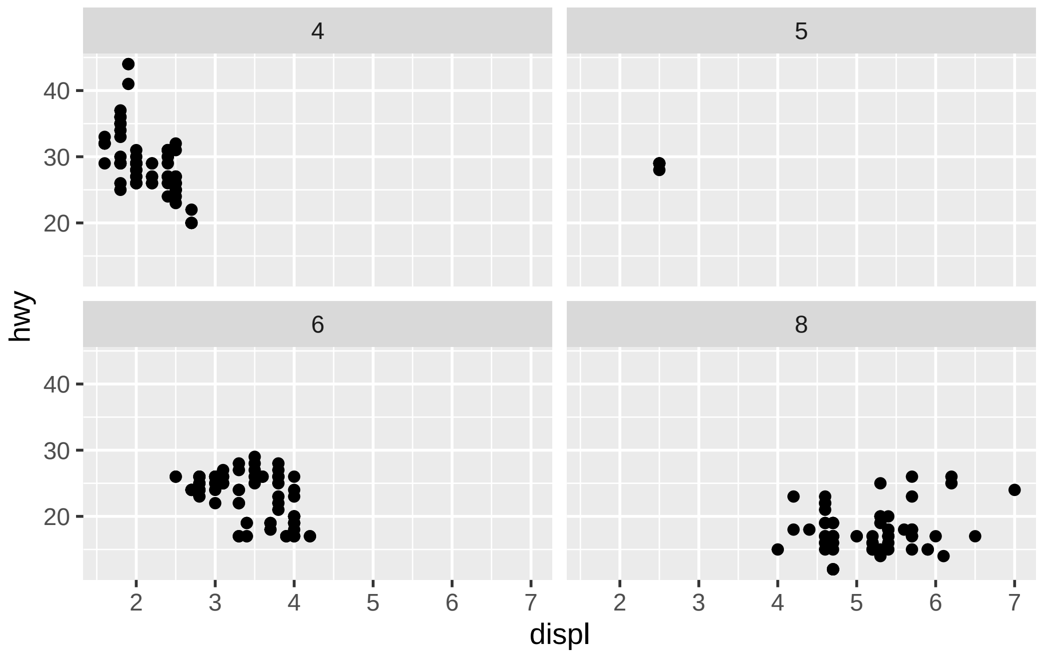
```r
ggplot(mpg, aes(x = displ, y = hwy, color = drv)) +
  geom_point() +
  geom_smooth(aes(linetype = drv))
```

```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```



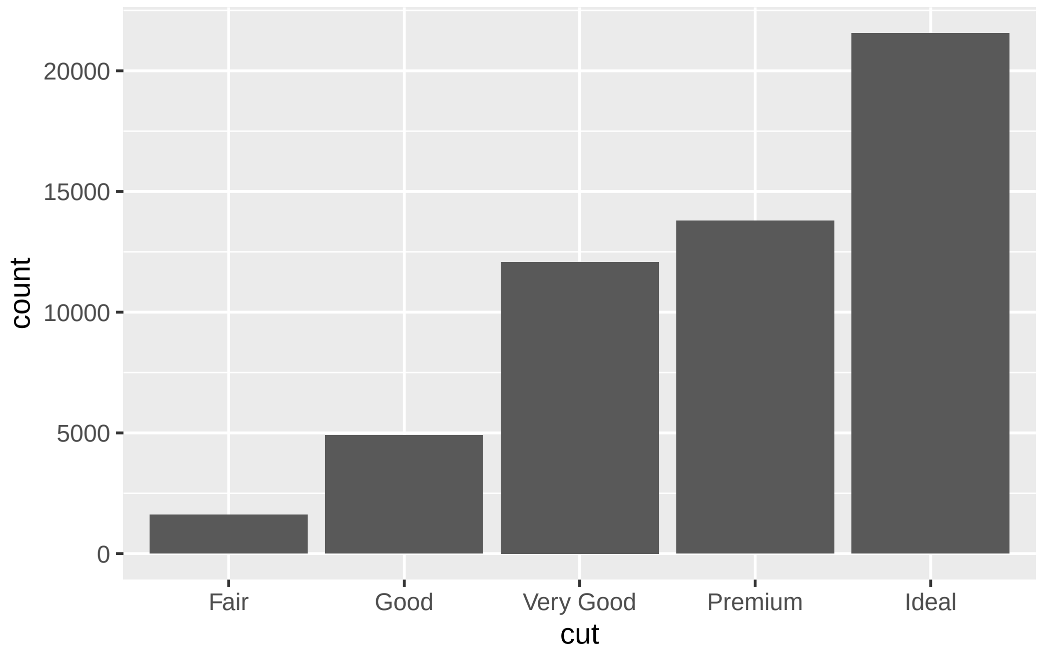
Example 3

```r
ggplot(mpg, aes(x = displ, y = hwy)) +
  geom_point() +
  facet_wrap(~cyl)
```



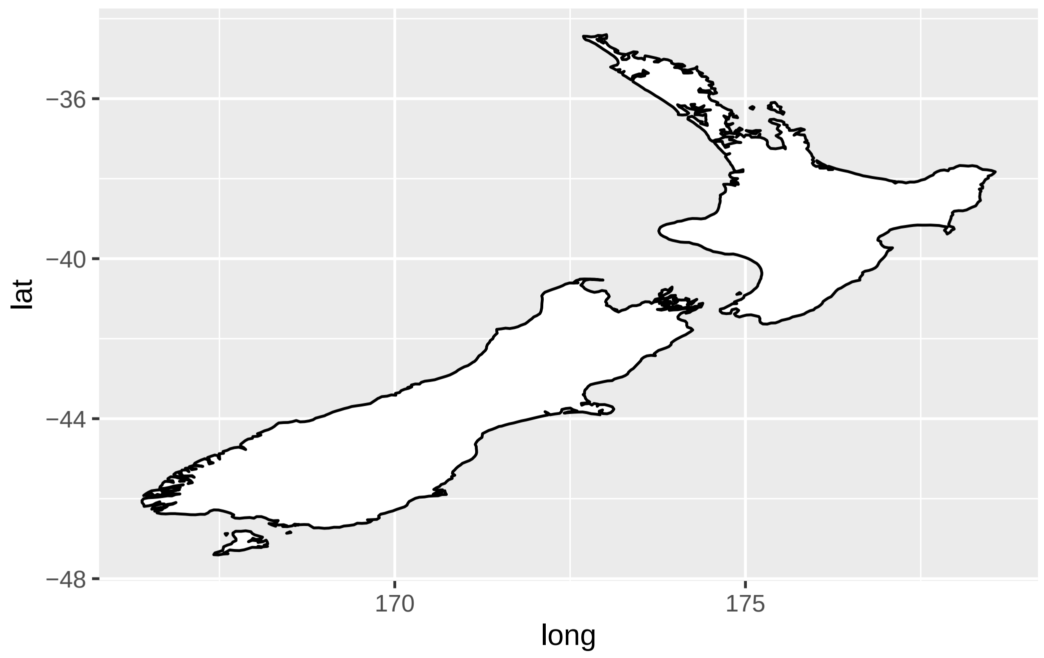
Example 4

```
ggplot(diamonds, aes(x = cut)) +
  geom_bar()
```

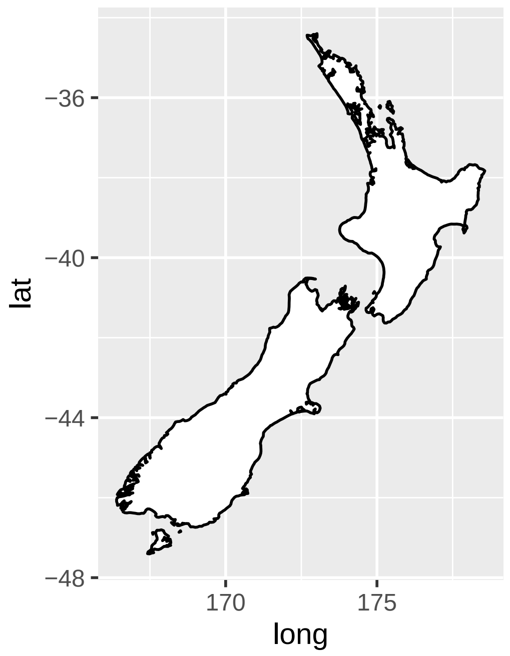


Example 5

```r
nz <- map_data("nz")
ggplot(nz, aes(x = long, y = lat, group = group)) +
  geom_polygon(fill = "white", color = "black")
```



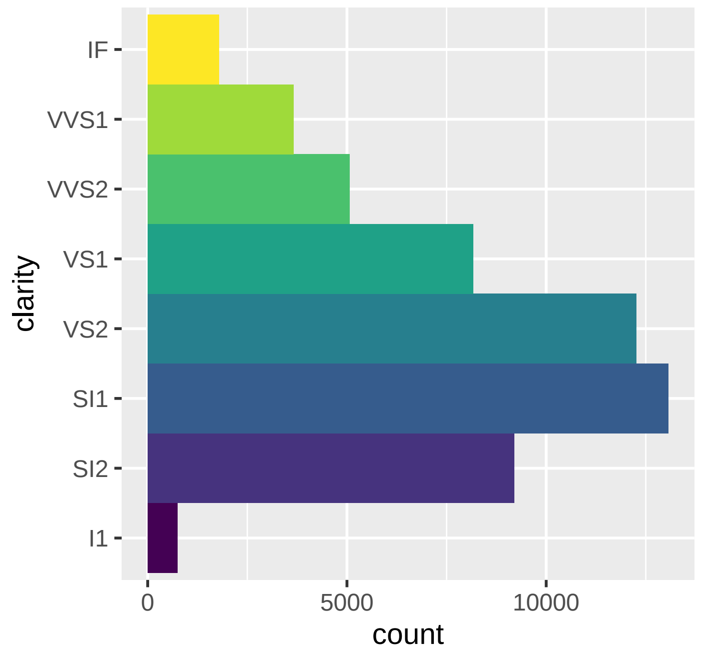
```r
ggplot(nz, aes(x = long, y = lat, group = group)) +
  geom_polygon(fill = "white", color = "black") +
  coord_quickmap()
```



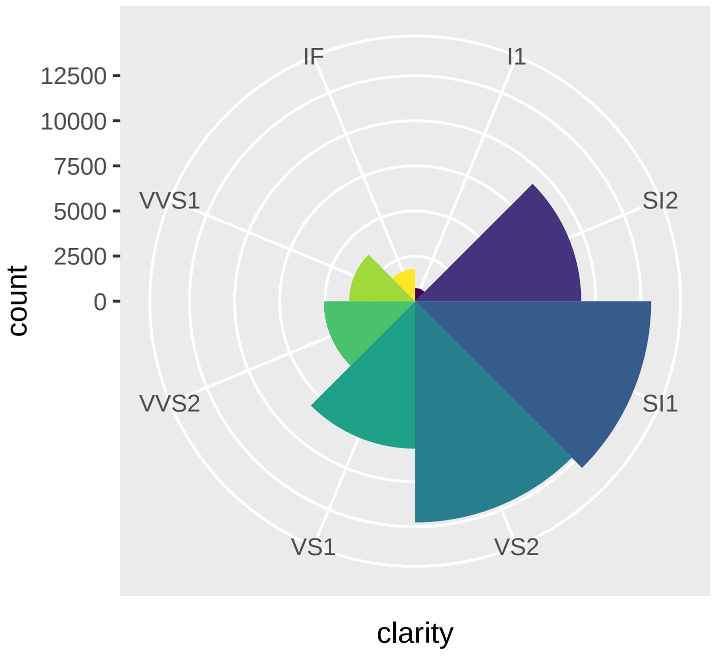
Example 6

```
bar <- ggplot(data = diamonds) +
  geom_bar(
    mapping = aes(x = clarity, fill = clarity),
    show.legend = FALSE,
    width = 1
  ) +
  theme(aspect.ratio = 1)

bar + coord_flip()
```



```r
bar + coord_polar()
```



Chapter 10: Exploratory Data Analysis (EDA)

This chapter focuses on exploratory data analysis, positioning visualization as a thinking tool rather than a presentation device. The chapter emphasizes that EDA is an iterative, creative and question-driven process.

The authors structure EDA around three core questions:

1. How do variables vary?
2. Are there unusual values?
3. How do variables covary?

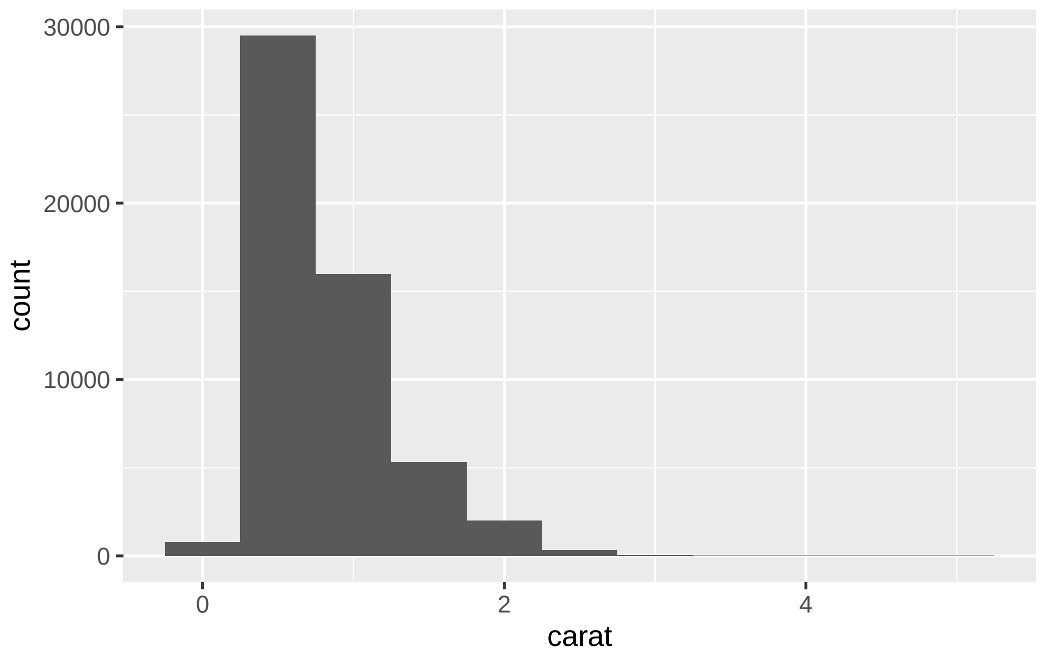
Through histograms, boxplots, scatterplots, and smooths, the chapter demonstrates how visualizations can uncover:

- Distributional shapes,
- Outliers and anomalies,
- Relationships between variables.

The chapter discourages premature modeling and instead promotes understanding the structure and quality of data first as reinforces the idea that good analysis begins with curiosity and skepticism, not assumptions.

Example 1

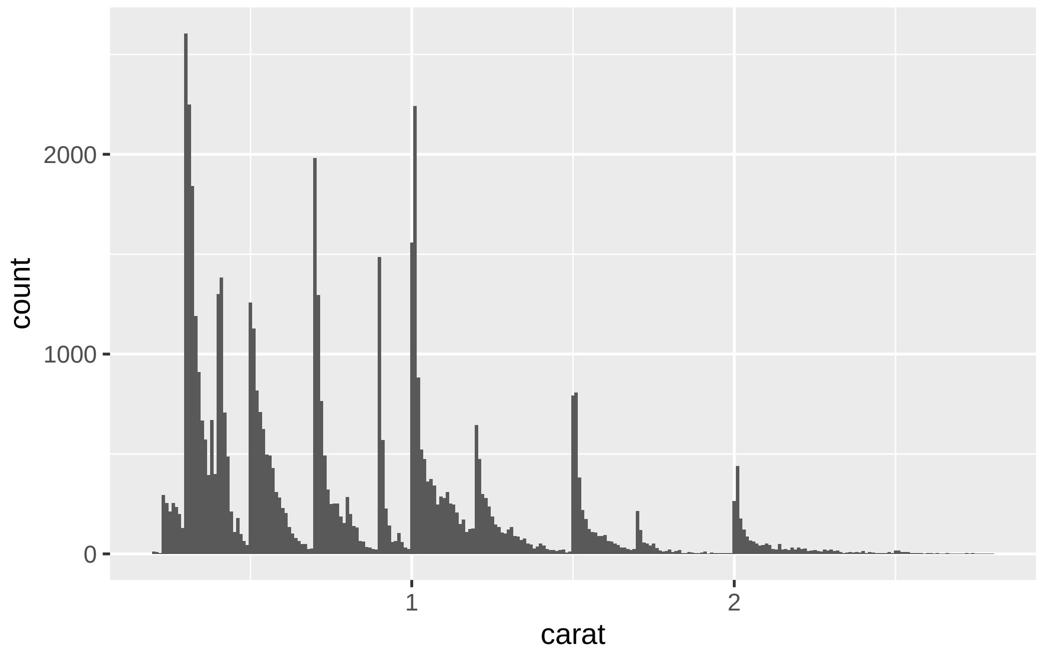
```r
ggplot(diamonds, aes(x = carat)) +
  geom_histogram(binwidth = 0.5)
```



Example 2

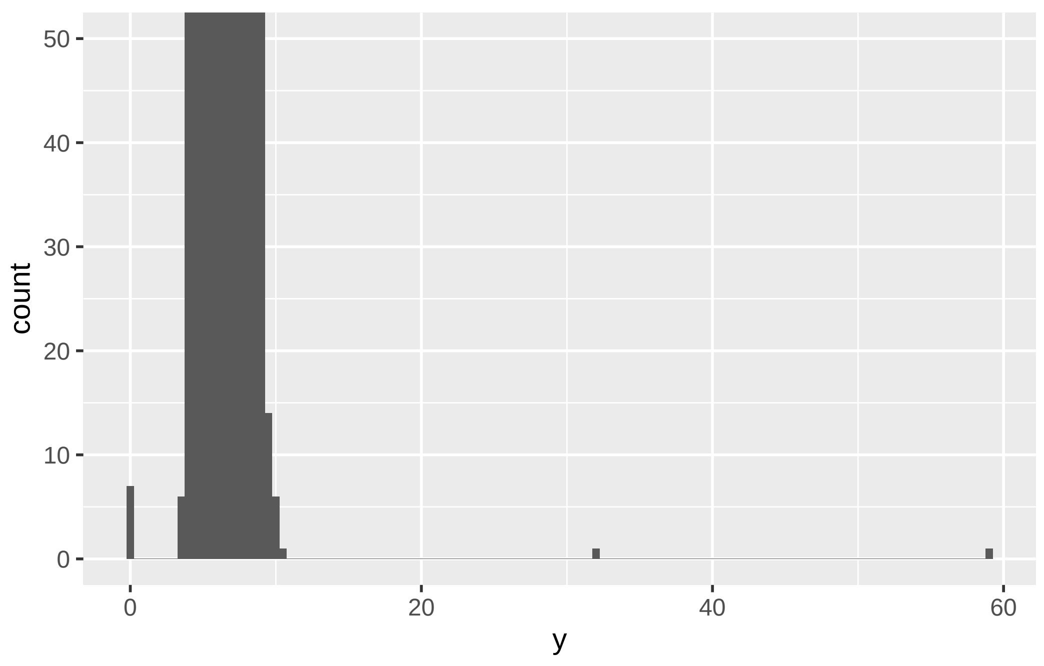
```
smaller <- diamonds |>
  filter(carat < 3)

ggplot(smaller, aes(x = carat)) +
  geom_histogram(binwidth = 0.01)
```



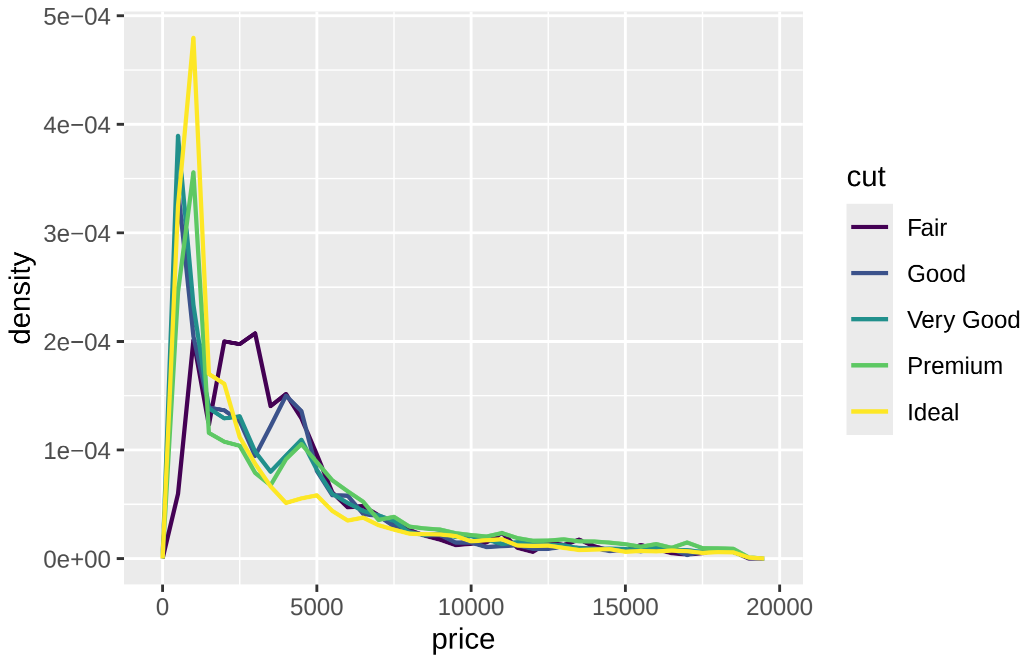
Example 3

```
ggplot(diamonds, aes(x = y)) +
  geom_histogram(binwidth = 0.5) +
  coord_cartesian(ylim = c(0, 50))
```



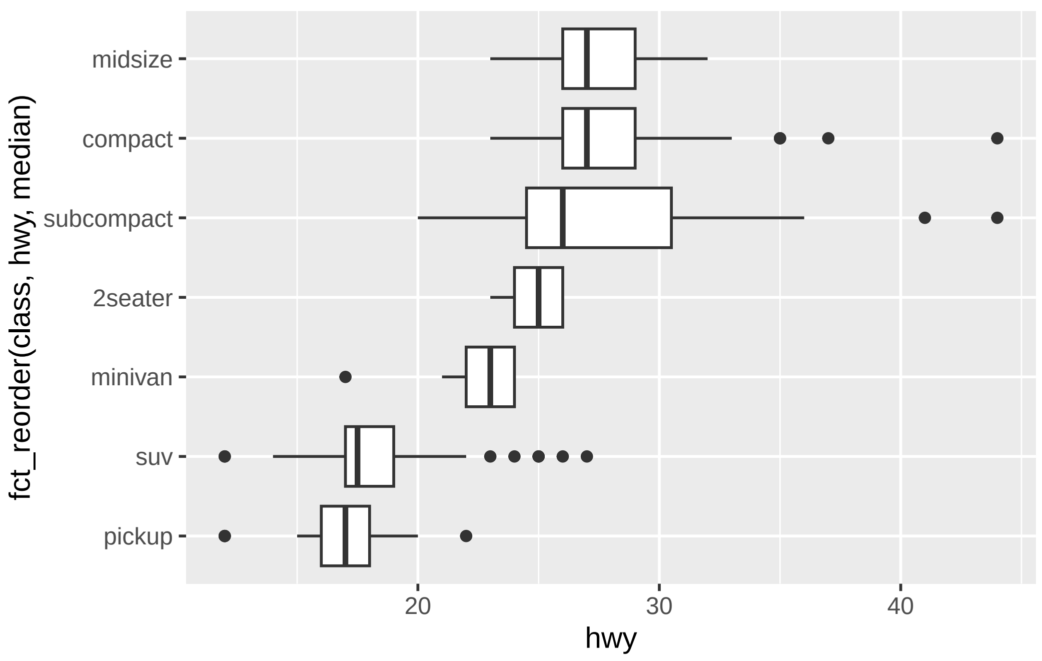
Example 4

```
ggplot(diamonds, aes(x = price, y = after_stat(density))) +
  geom_freqpoly(aes(color = cut), binwidth = 500, linewidth = 0.75)
```



Example 5

```
ggplot(mpg, aes(x = hwy, y = fct_reorder(class, hwy, median))) +
  geom_boxplot()
```



Chapter 11: Communication

This chapter explores effective communication by making insights understandable to others. The authors explain that communication-oriented graphics require different design choices than exploratory plots, placing more emphasis on:

- Clear and informative labels,
- Meaningful titles and subtitles,
- Thoughtful scale choices,
- Appropriate themes and layouts.

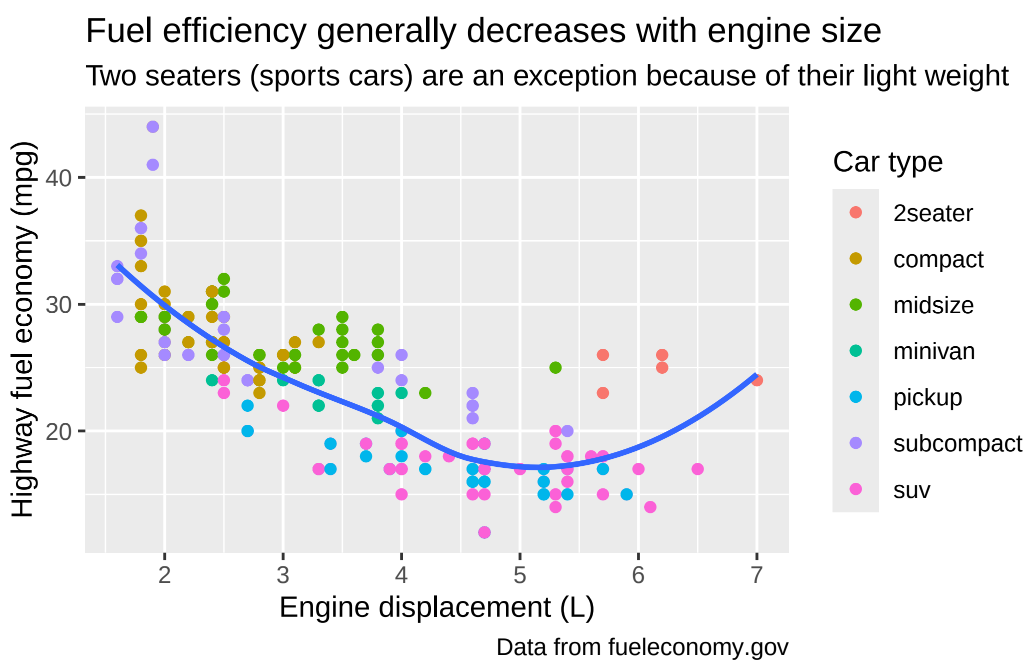
Annotations are introduced as tools for guiding interpretation, highlighting key patterns, or explaining anomalies. The chapter also discusses how consistent visual styling improves credibility and professionalism.

Ultimately, the chapter reinforces that analysis has little value if it cannot be communicated clearly, making visualization a core storytelling device in data science.

Example 1

```r
ggplot(mpg, aes(x = displ, y = hwy)) +
  geom_point(aes(color = class)) +
  geom_smooth(se = FALSE) +
  labs(
    x = "Engine displacement (L)",
    y = "Highway fuel economy (mpg)",
    color = "Car type",
    title = "Fuel efficiency generally decreases with engine size",
    subtitle = "Two seaters (sports cars) are an exception because of their light weight",
    caption = "Data from fueleconomy.gov"
  )
```

```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```



Example 2

```
label_info <- mpg |>
  group_by(drv) |>
  arrange(desc(displ)) |>
  slice_head(n = 1) |>
  mutate(
    drive_type = case_when(
      drv == "f" ~ "front-wheel drive",
      drv == "r" ~ "rear-wheel drive",
      drv == "4" ~ "4-wheel drive"
    )
  ) |>
  select(displ, hwy, drv, drive_type)

label_info
```

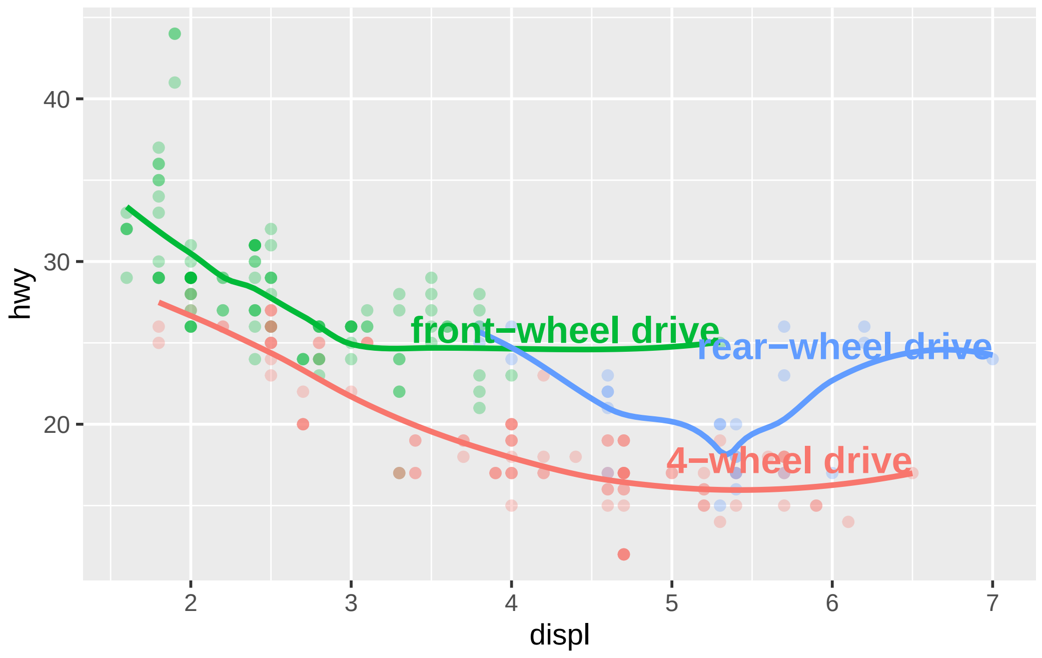
```
# A tibble: 3 x 4
# Groups:   drv [3]
  displ   hwy drv   drive_type
  <dbl> <int> <chr> <chr>
1   6.5    17 4     4-wheel drive
2   5.3    25 f     front-wheel drive
```

```
3   7        24 r      rear-wheel drive
```

Example 3

```
ggplot(mpg, aes(x = displ, y = hwy, color = drv)) +
  geom_point(alpha = 0.3) +
  geom_smooth(se = FALSE) +
  geom_text(
    data = label_info,
    aes(x = displ, y = hwy, label = drive_type),
    fontface = "bold", size = 5, hjust = "right", vjust = "bottom"
  ) +
  theme(legend.position = "none")
```

```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```



Chapter 12: Logical Vectors

This chapter focuses on logical vectors, which are fundamental to filtering, subsetting, and conditional logic in R. They are the simplest type of vectors because each element can only be of three possible values: TRUE, FALSE, and NA.

The chapter explains how comparisons produce logical values (TRUE or FALSE) and how these values can be combined using Boolean operators such as AND (&), OR (|), and NOT (!). These operations allow analysts to express complex rules for selecting data.

Logical vectors are then applied to summaries and conditional transformations, such as categorizing observations based on thresholds or conditions.

This chapter is crucial because logical thinking underpins nearly all data manipulation tasks. It formalizes the reasoning processes analysts intuitively use and translates them into precise, reproducible code.

Example 1

```r
library(tidyverse)
library(nycflights13)
x <- c(1, 2, 3, 5, 7, 11, 13)
x * 2
```

```
[1]  2  4  6 10 14 22 26
```

```r
df <- tibble(x)
df |>
  mutate(y = x * 2)
```

```
# A tibble: 7 x 2
      x     y
  <dbl> <dbl>
1     1     2
2     2     4
3     3     6
4     5    10
5     7    14
6    11    22
7    13    26
```

Example 2

```r
flights |>
  mutate(
    daytime = dep_time > 600 & dep_time < 2000,
    approx_ontime = abs(arr_delay) < 20,
  ) |>
  filter(daytime & approx_ontime)
```

```
# A tibble: 172,286 x 21
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013     1     1      601            600         1      844            850
 2  2013     1     1      602            610        -8      812            820
 3  2013     1     1      602            605        -3      821            805
 4  2013     1     1      606            610        -4      858            910
 5  2013     1     1      606            610        -4      837            845
 6  2013     1     1      607            607         0      858            915
 7  2013     1     1      611            600        11      945            931
 8  2013     1     1      613            610         3      925            921
 9  2013     1     1      615            615         0      833            842
10  2013     1     1      622            630        -8     1017           1014
# i 172,276 more rows
# i 13 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>, daytime <lgl>,
#   approx_ontime <lgl>
```

Example 3

```r
flights |>
  filter(arr_delay > 0) |>
  group_by(year, month, day) |>
  summarize(
    behind = mean(arr_delay),
    n = n(),
    .groups = "drop"
  )
```

```
# A tibble: 365 x 5
    year month   day behind     n
   <int> <int> <int>  <dbl> <int>
 1  2013     1     1   32.5   461
 2  2013     1     2   32.0   535
 3  2013     1     3   27.7   460
 4  2013     1     4   28.3   297
 5  2013     1     5   22.6   238
 6  2013     1     6   24.4   381
 7  2013     1     7   27.8   243
 8  2013     1     8   20.8   275
 9  2013     1     9   25.6   287
10  2013     1    10   27.3   220
# i 355 more rows
```

Chapter 13: Numbers

This chapter explores numeric data, focusing on how numbers are created, transformed, and summarized. Thus, strengthening quantitative literacy and prepares readers for both descriptive and inferential analysis.

The authors cover common numeric operations such as scaling, ranking, rounding, and aggregating. They emphasize the importance of understanding numeric precision, handling extreme values, and choosing appropriate summary statistics.

Numeric transformations are not purely mechanical; they encode analytical decisions. For instance, choosing a mean versus a median reflects assumptions about distribution and robustness.

```
library(tidyverse)
library(nycflights13)
```

Example 1

```
flights |> count(dest)
```

```
# A tibble: 105 x 2
   dest      n
   <chr> <int>
 1 ABQ     254
 2 ACK     265
 3 ALB     439
 4 ANC       8
 5 ATL   17215
 6 AUS    2439
 7 AVL     275
 8 BDL     443
 9 BGR     375
10 BHM     297
# i 95 more rows
```

Example2

```
flights |>
  group_by(dest) |>
  summarize(
    n = n(),
    delay = mean(arr_delay, na.rm = TRUE)
  )
```

```
# A tibble: 105 x 3
   dest      n delay
   <chr> <int> <dbl>
 1 ABQ     254  4.38
 2 ACK     265  4.85
 3 ALB     439 14.4 
 4 ANC       8 -2.5 
 5 ATL   17215 11.3 
 6 AUS    2439  6.02
 7 AVL     275  8.00
 8 BDL     443  7.05
 9 BGR     375  8.03
10 BHM     297 16.9 
# i 95 more rows
```

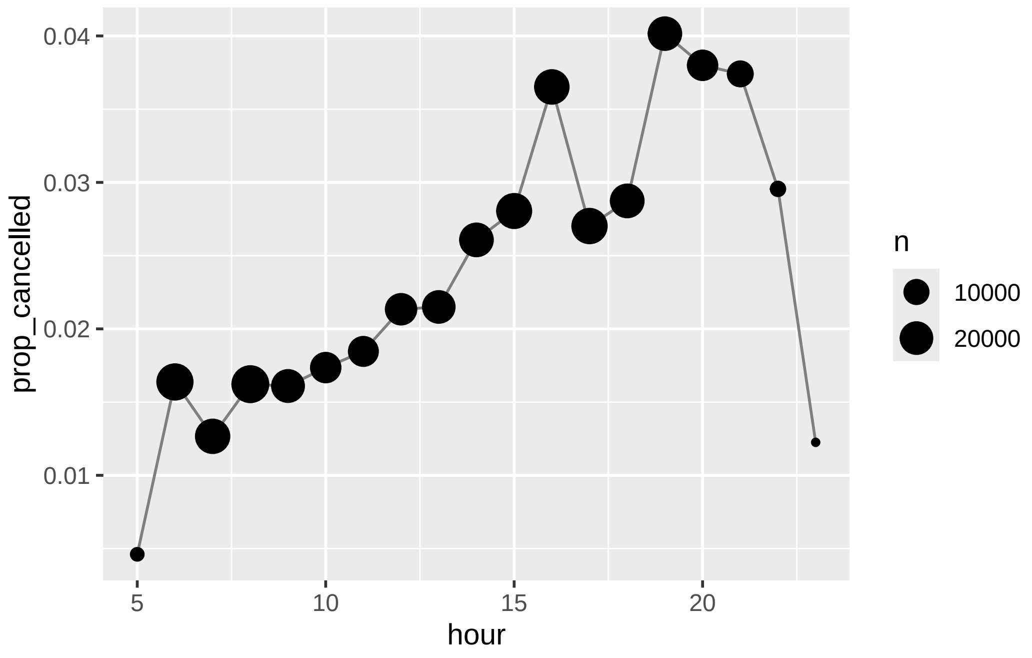
Example 3

```
flights |>
  group_by(dest) |>
  summarize(carriers = n_distinct(carrier)) |>
  arrange(desc(carriers))
```

```
# A tibble: 105 x 2
   dest  carriers
   <chr>    <int>
 1 ATL          7
 2 BOS          7
 3 CLT          7
 4 ORD          7
 5 TPA          7
 6 AUS          6
 7 DCA          6
 8 DTW          6
 9 IAD          6
10 MSP          6
# i 95 more rows
```

Example 4

```r
flights |>
  group_by(hour = sched_dep_time %/% 100) |>
  summarize(prop_cancelled = mean(is.na(dep_time)), n = n()) |>
  filter(hour > 1) |>
  ggplot(aes(x = hour, y = prop_cancelled)) +
  geom_line(color = "grey50") +
  geom_point(aes(size = n))
```



Chapter 14: Strings

This chapter addresses string data, which is pervasive in real-world datasets but often messy and inconsistent.

The chapter introduces the stringr package, which provides a consistent and readable interface for string operations. Topics include:

- Creating and combining strings,
- Detecting patterns,
- Extracting and modifying substrings.

The authors stress that text manipulation is essential for tasks such as cleaning names, parsing identifiers, and standardizing categorical values.

Example 1

```r
library(tidyverse)
library(babynames)
string1 <- "R is fascinating"
string2 <- 'It is best for statistical analysis'
string1
```

```
[1] "R is fascinating"
```

```r
string2
```

```
[1] "It is best for statistical analysis"
```

Example 2

```r
str_c("x", "y")
```

```
[1] "xy"
```

```r
str_c("x", "y", "z")
```

```
[1] "xyz"
```

```r
str_c("Hello ", c("John", "Susan"))
```

```
[1] "Hello John"  "Hello Susan"
```

Example 3

```r
str_c("x", "y")
```

```
[1] "xy"
```

```r
str_c("x", "y", "z")
```

```
[1] "xyz"
```

```r
str_c("Hello ", c("John", "Susan"))
```

```
[1] "Hello John"  "Hello Susan"
```

Example 4

```r
df1 <- tibble(x = c("a,b,c", "d,e", "f"))
df1 |>
  separate_longer_delim(x, delim = ",")
```

```
# A tibble: 6 x 1
  x
  <chr>
1 a
2 b
3 c
4 d
5 e
6 f
```

Example 5

```
df2 <- tibble(x = c("1211", "131", "21"))
df2 |>
  separate_longer_position(x, width = 1)
```

```
# A tibble: 9 x 1
  x
  <chr>
1 1
2 2
3 1
4 1
5 1
6 3
7 1
8 2
9 1
```

Chapter 15: Regular Expressions

This chapter builds on chapter 14 by introducing regular expressions (regex), a powerful language for pattern matching.

Rather than presenting regex as an abstract formalism, the authors focus on practical usage: detecting patterns, extracting components, and validating text formats.

The chapter also acknowledges the cognitive difficulty of regex and encourages gradual mastery through practice and reference rather than memorization. Regular expressions are positioned as a force multiplier, enabling analysts to solve complex text problems concisely and efficiently.

Example 1

```r
library(tidyverse)
library(babynames)
str_view(fruit, "berry")
```

```
 [6] │ bil<berry>
 [7] │ black<berry>
[10] │ blue<berry>
[11] │ boysen<berry>
[19] │ cloud<berry>
[21] │ cran<berry>
[29] │ elder<berry>
[32] │ goji <berry>
[33] │ goose<berry>
[38] │ huckle<berry>
[50] │ mul<berry>
[70] │ rasp<berry>
[73] │ salal <berry>
[76] │ straw<berry>
```

Example 2

```r
str_view(c("a", "ab", "ae", "bd", "ea", "eab"), "a.")
```

```
[2] │ <ab>
[3] │ <ae>
[6] │ e<ab>
```

Example 3

```r
str_view(c("a", "ab", "abb"), "ab?")
```

```
[1] | <a>
[2] | <ab>
[3] | <ab>b
```

Example 4

```r
str_detect(c("a", "b", "c"), "[aeiou]")
```

```
[1]  TRUE FALSE FALSE
```

Example 5

```r
babynames |>
  filter(str_detect(name, "x")) |>
  count(name, wt = n, sort = TRUE)
```

```
# A tibble: 974 x 2
   name            n
   <chr>       <int>
 1 Alexander  665492
 2 Alexis     399551
 3 Alex       278705
 4 Alexandra  232223
 5 Max        148787
 6 Alexa      123032
 7 Maxine     112261
 8 Alexandria  97679
 9 Maxwell     90486
10 Jaxon       71234
# i 964 more rows
```

Chapter 16: Factors

This chapter focuses on categorical data, represented in R as factors.

The chapter explains why factors exist: they encode not just values, but also order and reference levels, which directly affect summaries, models, and visualizations.

It teaches us how to:

- Reorder factor levels,
- Relabel categories,
- Work with ordered factors.

Example 1

```
library(tidyverse)
x1 <- c("Dec", "Apr", "Jan", "Mar")
x1
```

```
[1] "Dec" "Apr" "Jan" "Mar"
```

```
sort(x1)
```

```
[1] "Apr" "Dec" "Jan" "Mar"
```

```
factor(x1)
```

```
[1] Dec Apr Jan Mar
Levels: Apr Dec Jan Mar
```

```
fct(x1)
```

```
[1] Dec Apr Jan Mar
Levels: Dec Apr Jan Mar
```

Example 2

```
month_levels <- c(
  "Jan", "Feb", "Mar", "Apr", "May", "Jun",
  "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"
)
month_levels
```

```
 [1] "Jan" "Feb" "Mar" "Apr" "May" "Jun" "Jul" "Aug" "Sep" "Oct" "Nov" "Dec"
```

```
y1 <- factor(x1, levels = month_levels)
y1
```

```
[1] Dec Apr Jan Mar
Levels: Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
```

```
sort(y1)
```

```
[1] Jan Mar Apr Dec
Levels: Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
```

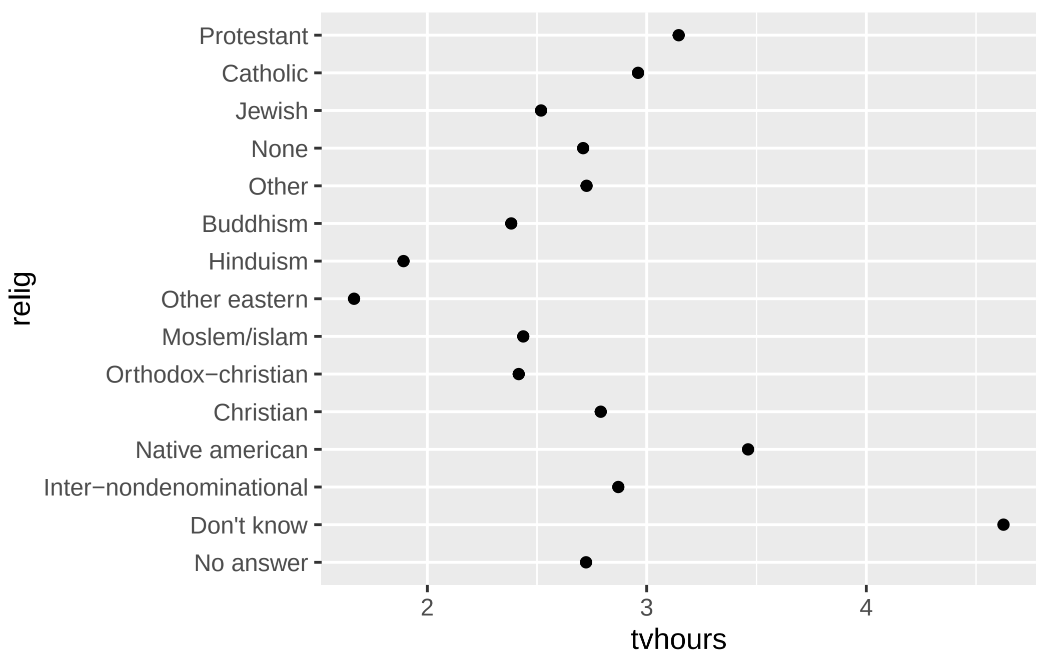
Example 3

```
gss_cat |>
  count(race)
```

```
# A tibble: 3 x 2
  race      n
  <fct> <int>
1 Other  1959
2 Black  3129
3 White 16395
```

```
relig_summary <- gss_cat |>
  group_by(relig) |>
  summarize(
    tvhours = mean(tvhours, na.rm = TRUE),
    n = n()
  )

ggplot(relig_summary, aes(x = tvhours, y = relig)) +
  geom_point()
```


Protestant
Catholic
Jewish
None
Other
Buddhism
Hinduism
Other eastern
Moslem/islam
Orthodox−christian
Christian
Native american
Inter−nondenominational
Don't know
No answer
relig
2
3
4
tvhours

Chapter 17: Dates and Times

This chapter addresses temporal data, one of the most complex data types to handle correctly.

Using the `lubridate` package, the authors explain how to parse dates and datetimes, extract components, calculate time spans, and handle time zones.

The chapter highlights common pitfalls, such as ambiguous date formats and daylight saving time issues, reinforcing the need for explicit and careful handling of time.

This chapter equips us with expertise to analyze trends, durations, and seasonality with confidence.

Example 1

```r
library(tidyverse)
library(nycflights13)
today()
```

```
[1] "2025-12-19"
```

```r
now()
```

```
[1] "2025-12-19 20:19:53 UTC"
```

Example 2

```r
csv <- "
  date,datetime
  2022-01-02,2022-01-02 05:12
"
read_csv(csv)
```

```
Rows: 1 Columns: 2
-- Column specification --------------------------------------------------------
Delimiter: ","
dttm (1): datetime
date (1): date

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
# A tibble: 1 x 2
  date       datetime
  <date>     <dttm>
1 2022-01-02 2022-01-02 05:12:00
```

Example 3

```
csv <- "
  date
  01/02/15
"

read_csv(csv, col_types = cols(date = col_date("%m/%d/%y")))
```

```
# A tibble: 1 x 1
  date
  <date>
1 2015-01-02
```

```
read_csv(csv, col_types = cols(date = col_date("%d/%m/%y")))
```

```
# A tibble: 1 x 1
  date
  <date>
1 2015-02-01
```

```
read_csv(csv, col_types = cols(date = col_date("%y/%m/%d")))
```

```
# A tibble: 1 x 1
  date
  <date>
1 2001-02-15
```

Example 4

```
ymd("2017-01-31")
```

```
[1] "2017-01-31"
```

```r
mdy("January 31st, 2017")
```

```
[1] "2017-01-31"
```

```r
dmy("31-Jan-2017")
```

```
[1] "2017-01-31"
```

Example 5

```r
flights |>
  select(year, month, day, hour, minute)
```

```
# A tibble: 336,776 x 5
    year month   day  hour minute
   <int> <int> <int> <dbl>  <dbl>
 1  2013     1     1     5     15
 2  2013     1     1     5     29
 3  2013     1     1     5     40
 4  2013     1     1     5     45
 5  2013     1     1     6      0
 6  2013     1     1     5     58
 7  2013     1     1     6      0
 8  2013     1     1     6      0
 9  2013     1     1     6      0
10  2013     1     1     6      0
# i 336,766 more rows
```

Chapter 18: Missing Values

This chapter focuses entirely on **missing data**, treating it as an analytical issue rather than a nuisance.

The authors distinguish between:

- Explicit missing values (NA),
- Implicit missing values (absent combinations).

They explain how missingness can bias summaries and models if handled carelessly and demonstrate tidyverse tools for identifying, removing, or explicitly representing missing data.

The chapter emphasizes transparency and intentionality in handling missing values.

Example 1

```r
library(tidyverse)
treatment <- tribble(
  ~person,           ~treatment, ~response,
  "Derrick Whitmore", 1,         7,
  NA,                 2,         10,
  NA,                 3,         NA,
  "Katherine Burke",  1,         4
)
treatment
```

```
# A tibble: 4 x 3
  person           treatment response
  <chr>                <dbl>    <dbl>
1 Derrick Whitmore         1        7
2 <NA>                     2       10
3 <NA>                     3       NA
4 Katherine Burke          1        4
```

Example 2

```r
treatment |>
  fill(everything())
```

```
# A tibble: 4 x 3
  person           treatment response
  <chr>                <dbl>    <dbl>
1 Derrick Whitmore         1        7
2 Derrick Whitmore         2       10
3 Derrick Whitmore         3       10
4 Katherine Burke          1        4
```

Example 3

```r
x <- c(1, 4, 5, 7, NA)
coalesce(x, 0)
```

```
[1] 1 4 5 7 0
```

Example 4

```r
x <- c(1, 4, 5, 7, -99)
na_if(x, -99)
```

```
[1]  1  4  5  7 NA
```

Chapter 19: Joins

This covers **joining data tables**, a fundamental operation in relational data analysis.

The chapter explains keys, relationships, and different types of joins (left, right, inner, full). It also explores how joins work conceptually and why they sometimes produce unexpected results.

Non-equi joins are introduced for advanced matching scenarios.

This chapter equips readers to combine datasets accurately and confidently, a critical skill in applied data science.

Example 1

```r
library(tidyverse)
library(nycflights13)
planes |>
  count(tailnum) |>
  filter(n > 1)
```

```
# A tibble: 0 x 2
# i 2 variables: tailnum <chr>, n <int>
```

```r
weather |>
  count(time_hour, origin) |>
  filter(n > 1)
```

```
# A tibble: 0 x 3
# i 3 variables: time_hour <dttm>, origin <chr>, n <int>
```

Example 2

```r
planes |>
  filter(is.na(tailnum))
```

```
# A tibble: 0 x 9
# i 9 variables: tailnum <chr>, year <int>, type <chr>, manufacturer <chr>,
#   model <chr>, engines <int>, seats <int>, speed <int>, engine <chr>
```

```r
weather |>
  filter(is.na(time_hour) | is.na(origin))
```

```
# A tibble: 0 x 15
# i 15 variables: origin <chr>, year <int>, month <int>, day <int>, hour <int>,
#   temp <dbl>, dewp <dbl>, humid <dbl>, wind_dir <dbl>, wind_speed <dbl>,
#   wind_gust <dbl>, precip <dbl>, pressure <dbl>, visib <dbl>,
#   time_hour <dttm>
```

Example 3

```r
flights |>
  count(time_hour, carrier, flight) |>
  filter(n > 1)
```

```
# A tibble: 0 x 4
# i 4 variables: time_hour <dttm>, carrier <chr>, flight <int>, n <int>
```

Example 4

```r
airports |>
  count(alt, lat) |>
  filter(n > 1)
```

```
# A tibble: 1 x 3
    alt   lat     n
  <dbl> <dbl> <int>
1    13  40.6     2
```

Chapter 20: Spreadsheets

This chapter addresses importing data from spreadsheets, acknowledging that Excel and Google Sheets remain dominant data storage formats.

The chapter explains how to read, write, and manage spreadsheet data using R, while also warning about common spreadsheet issues such as hidden types, merged cells, and inconsistent formatting.

It bridges the gap between real-world data practices and reproducible analysis, reinforcing R's role as an analytical backbone rather than a replacement for spreadsheets.

Example 1

```
library(readxl)
library(tidyverse)
library(writexl)
students <- read_excel("students.xlsx")
students
```

```
# A tibble: 6 x 5
  `Student ID` `Full Name`      favourite.food     mealPlan            AGE
         <dbl> <chr>            <chr>              <chr>               <chr>
1            1 Sunil Huffmann   Strawberry yoghurt Lunch only          4.0
2            2 Barclay Lynn     French fries       Lunch only          5.0
3            3 Jayendra Lyne    N/A                Breakfast and lunch 7.0
4            4 Leon Rossini     Anchovies          Lunch only          <NA>
5            5 Chidiegwu Dunkel Pizza              Breakfast and lunch five
6            6 Güvenç Attila    Ice cream          Lunch only          6.0
```

Example 2

```
read_excel(
  "students.xlsx",
  col_names = c("student_id", "full_name", "favourite_food", "meal_plan", "age"),
  skip = 1
)
```

```
# A tibble: 6 x 5
  student_id full_name        favourite_food     meal_plan           age
       <dbl> <chr>            <chr>              <chr>               <chr>
1          1 Sunil Huffmann   Strawberry yoghurt Lunch only          4.0
2          2 Barclay Lynn     French fries       Lunch only          5.0
```

```
3           3 Jayendra Lyne    N/A                Breakfast and lunch 7.0
4           4 Leon Rossini     Anchovies          Lunch only          <NA>
5           5 Chidiegwu Dunkel Pizza              Breakfast and lunch five
6           6 Güvenç Attila    Ice cream          Lunch only          6.0
```

Example 3

```r
students <- read_excel(
  "students.xlsx",
  col_names = c("student_id", "full_name", "favourite_food", "meal_plan", "age"),
  skip = 1,
  na = c("", "N/A"),
  col_types = c("numeric", "text", "text", "text", "text")
)

students <- students |>
  mutate(
    age = if_else(age == "five", "5", age),
    age = parse_number(age)
  )

students
```

```
# A tibble: 6 x 5
  student_id full_name        favourite_food     meal_plan             age
       <dbl> <chr>            <chr>              <chr>               <dbl>
1          1 Sunil Huffmann   Strawberry yoghurt Lunch only              4
2          2 Barclay Lynn     French fries       Lunch only              5
3          3 Jayendra Lyne    <NA>               Breakfast and lunch     7
4          4 Leon Rossini     Anchovies          Lunch only             NA
5          5 Chidiegwu Dunkel Pizza              Breakfast and lunch     5
6          6 Güvenç Attila    Ice cream          Lunch only              6
```

Example 4

```r
bake_sale <- tibble(
  item     = factor(c("brownie", "cupcake", "cookie")),
  quantity = c(10, 5, 8)
)

bake_sale
```

```
# A tibble: 3 x 2
  item    quantity
  <fct>      <dbl>
1 brownie       10
2 cupcake        5
3 cookie         8
```

Example 5

```r
write_xlsx(bake_sale, path = "bake-sale.xlsx")
read_excel("bake-sale.xlsx")
```

```
# A tibble: 3 x 2
  item    quantity
  <chr>      <dbl>
1 brownie       10
2 cupcake        5
3 cookie         8
```

Conclusion

To sum up, the first 20 chapters of R for Data Science have provided a comprehensive and coherent foundation for understanding both the philosophy and practice of modern data science using R. These chapters go well beyond introducing tools; they present data science as an end-to-end, iterative process that begins with data acquisition and preparation, advances through transformation, exploration, and visualization, and is anchored by sound workflow practices and reproducible principles.

Wickham, Hadley, Mine Çetinkaya-Rundel, and Garrett Grolemund. 2023. *R for Data Science: Import, Tidy, Transform, Visualize, and Model Data.* 2nd ed. Sebastopol, CA: O'Reilly Media. https://r4ds.hadley.nz.