Assignment 3

A Summary of Chapters 8–20

R for Data Science by Hadley Wickham and Garrett Grolemund

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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:

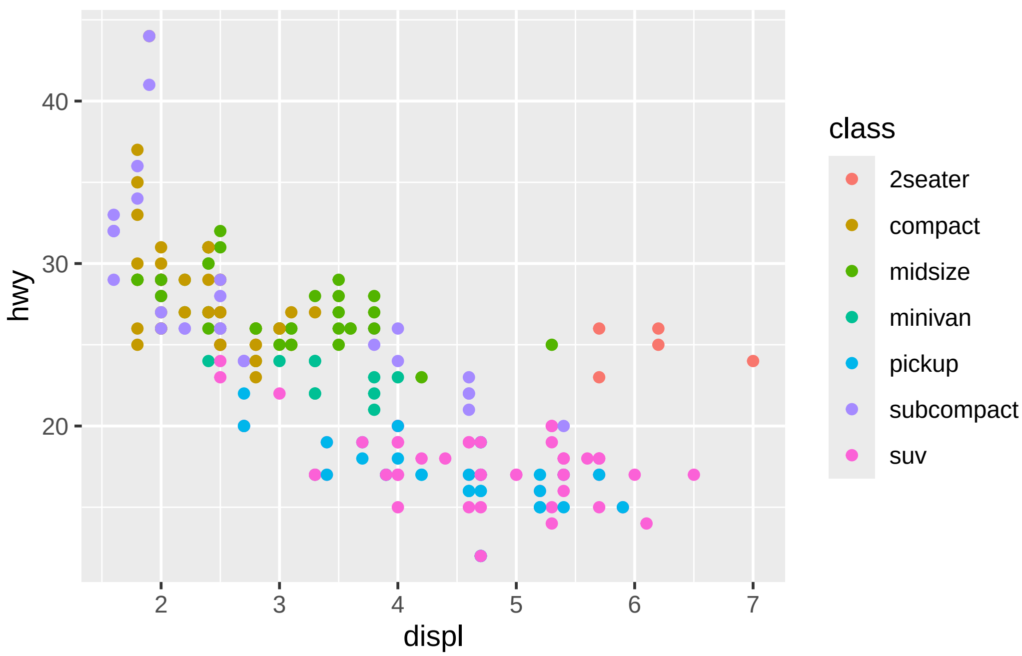
- **Facets**, which split data into subplots for comparison,
- **Statistical transformations**, which summarize or model data before plotting,
- **Positional adjustments,** which affects how the data is positioned.
- **Coordinate systems**, which affect how data are projected onto the plotting space.

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 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 becom
```

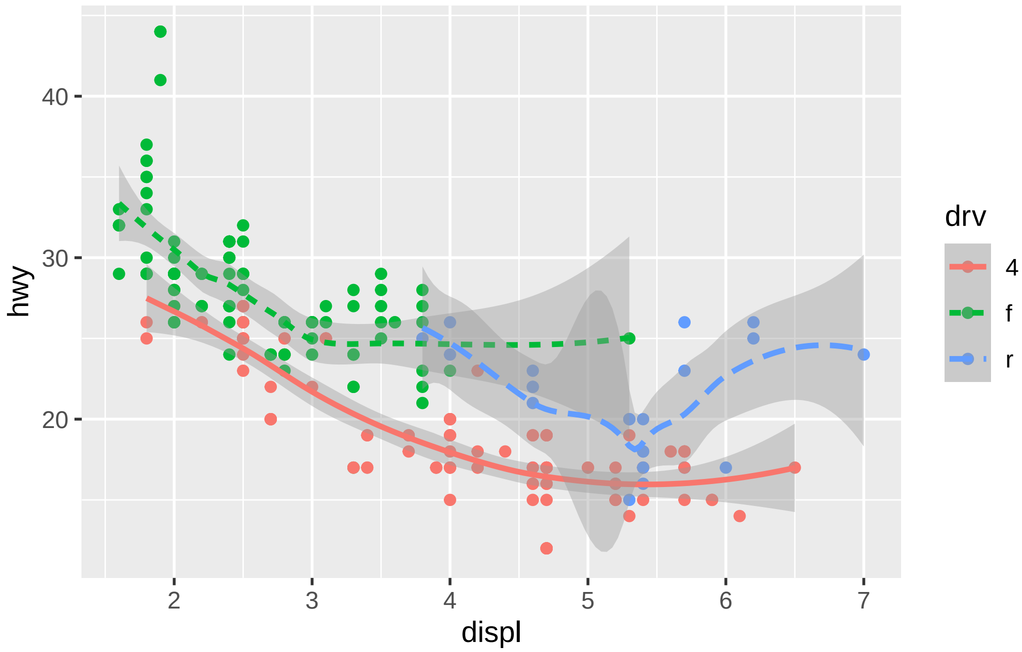
```r
ggplot(mpg, aes(x = displ, y = hwy, color = class)) +
  geom_point()
```



Example 2

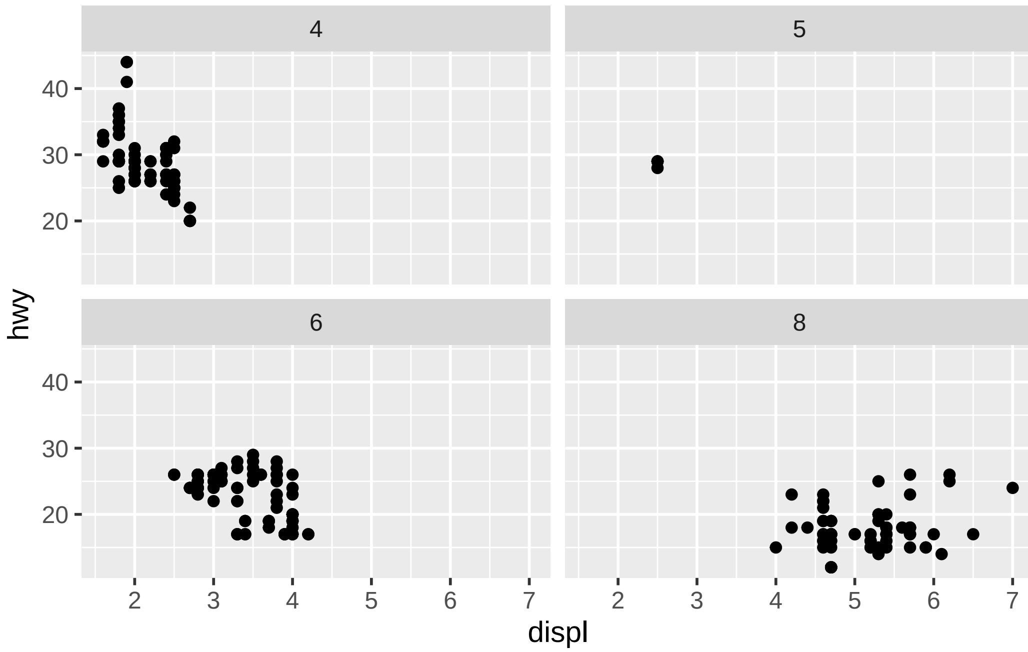
```
ggplot(mpg, aes(x = displ, y = hwy, color = drv)) +
  geom_point() +
  geom_smooth(aes(linetype = drv))
```

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



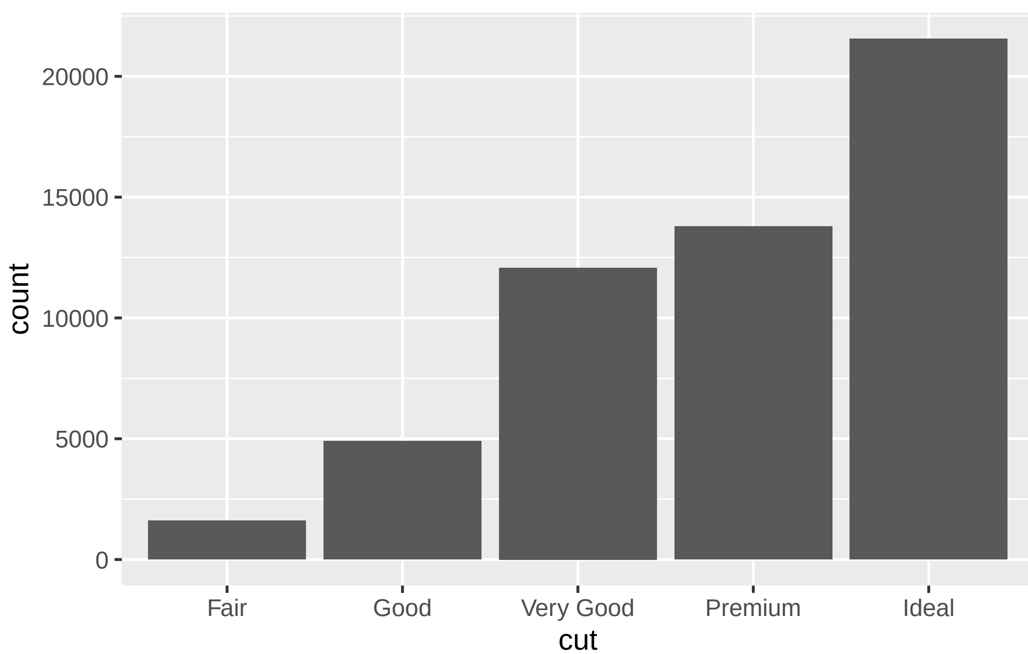
Example 3

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



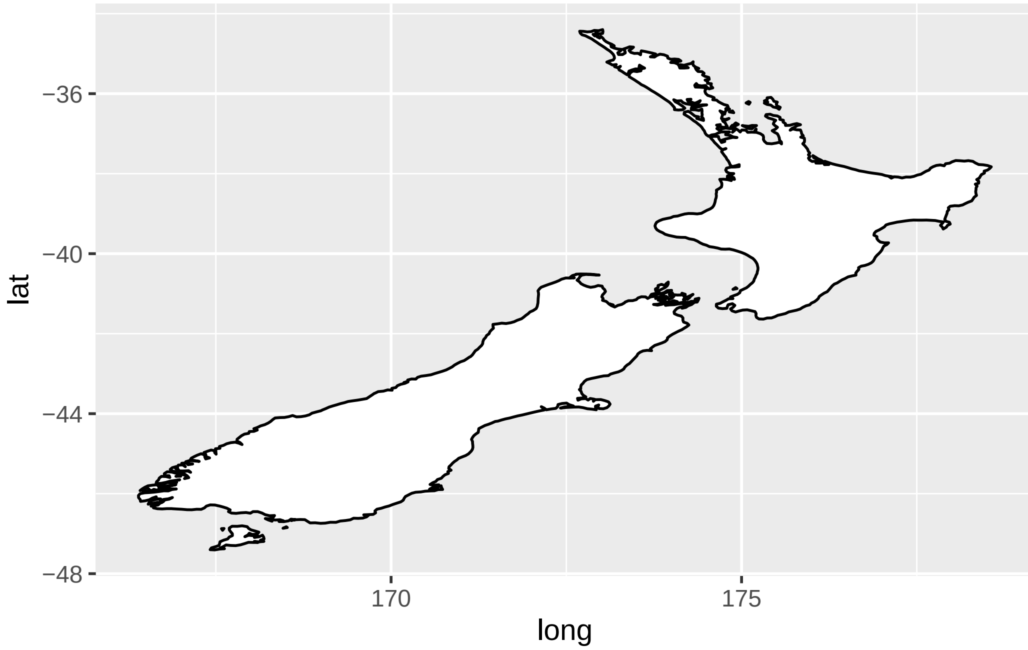
Example 4

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

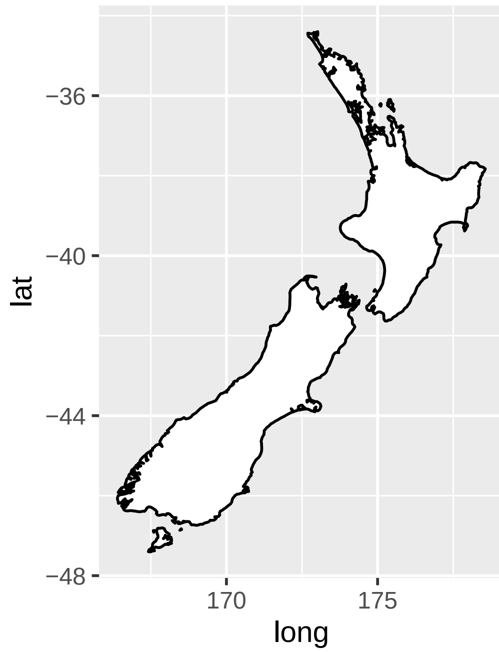


Example 5

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



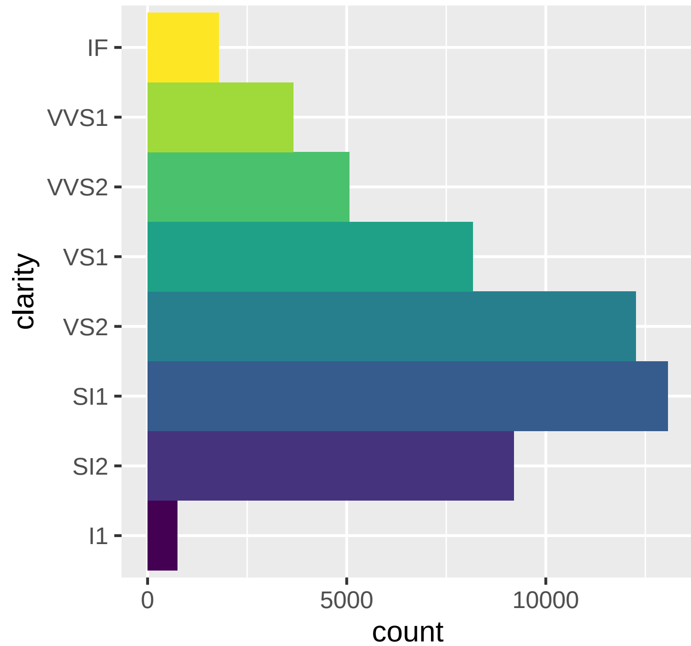

```
ggplot(nz, aes(x = long, y = lat, group = group)) +
  geom_polygon(fill = "white", color = "black") +
  coord_quickmap()
```



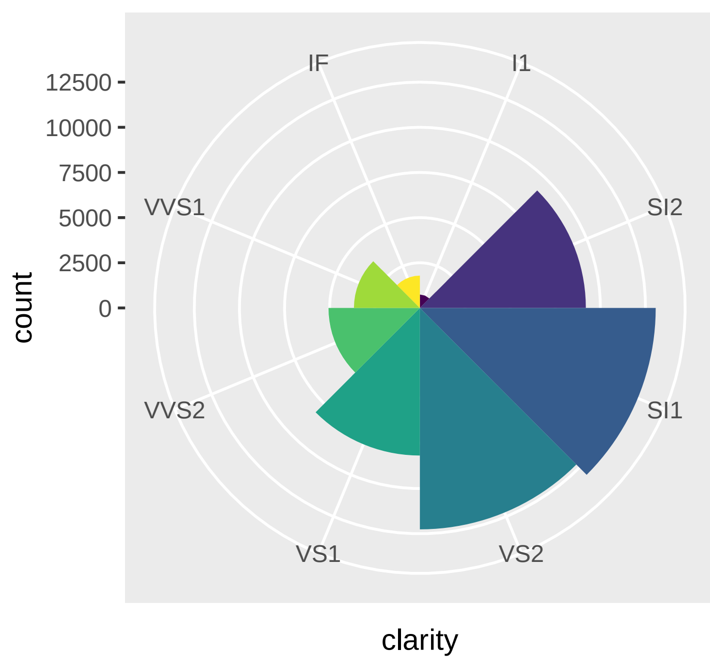
Example 6

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

bar + coord_flip()
```




```
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?

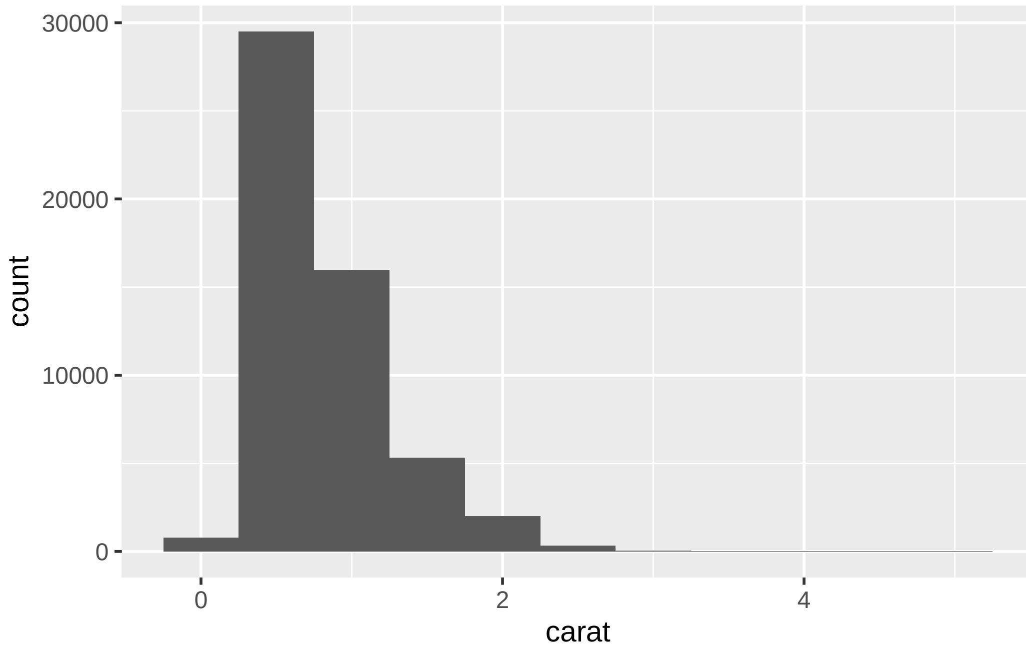
Through histograms, boxplots, scatterplots, and smooths, the chapter demonstrates how visualizations can uncover:

- 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

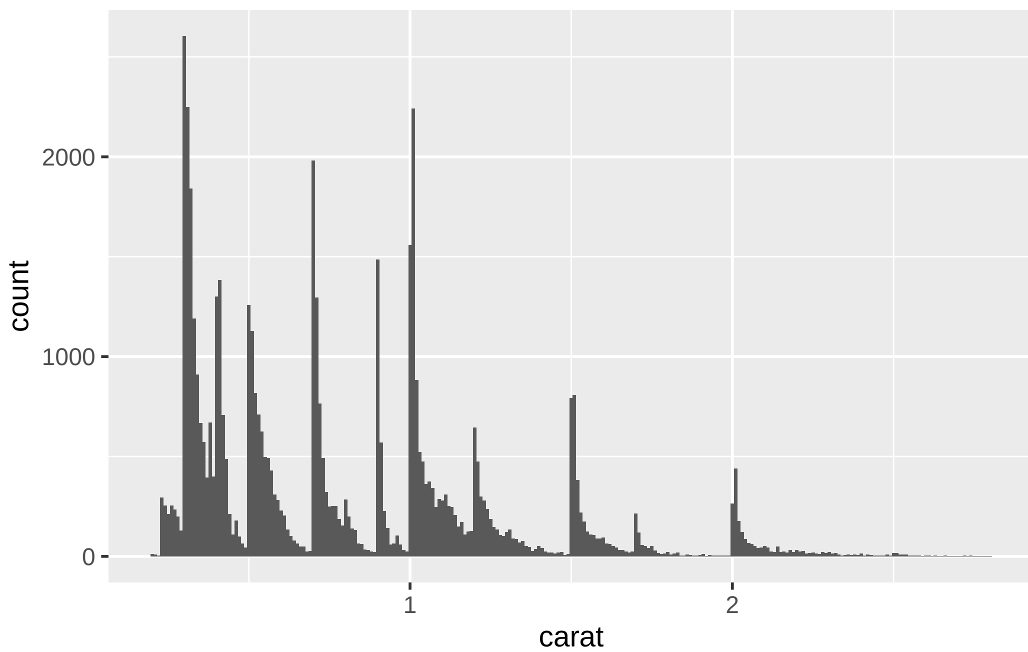
```
ggplot(diamonds, aes(x = carat)) +
  geom_histogram(binwidth = 0.5)
```



Example 2

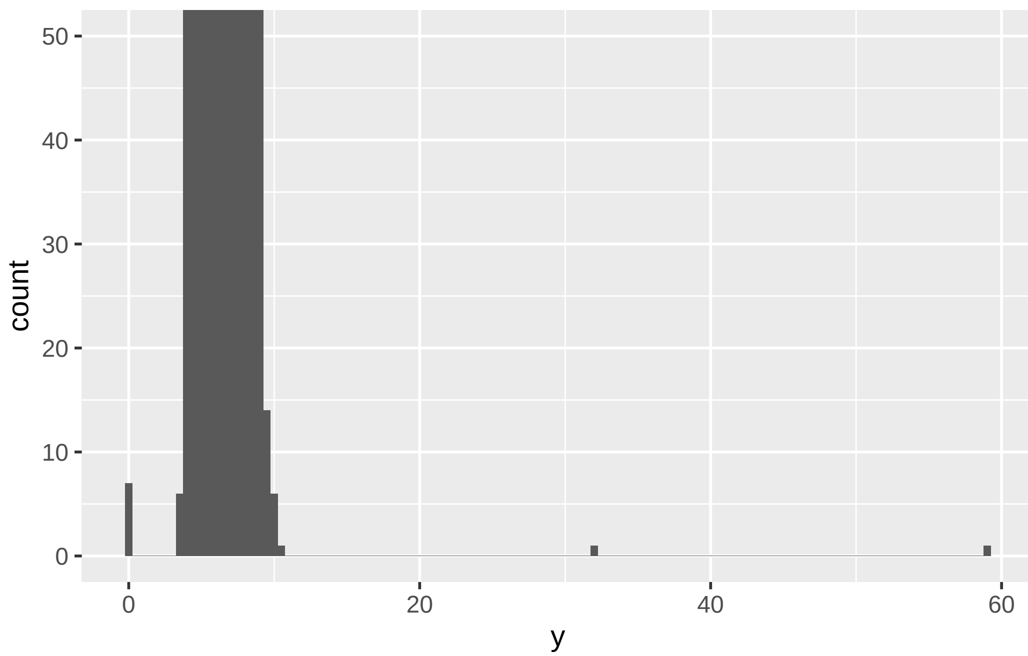
```
smaller <- diamonds |>
  filter(carat < 3)

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



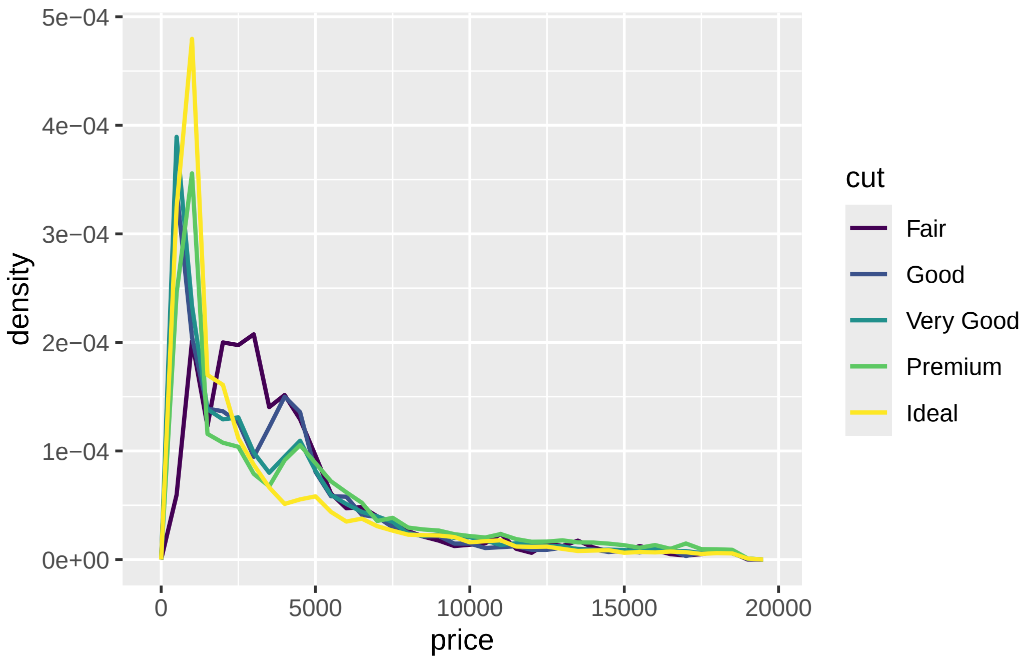
Example 3

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



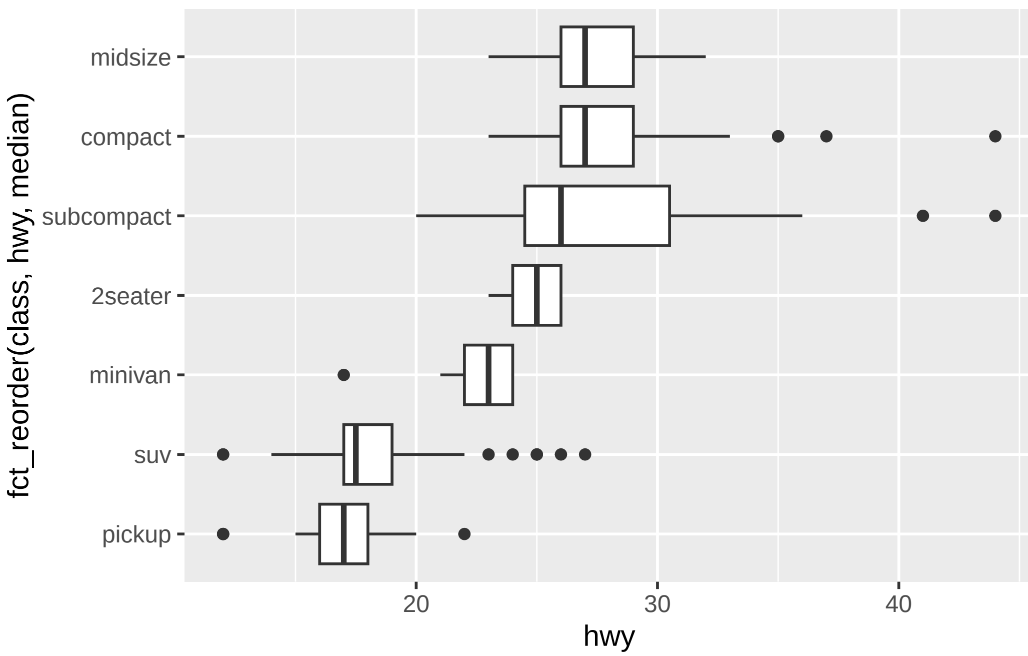
Example 4

```
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.

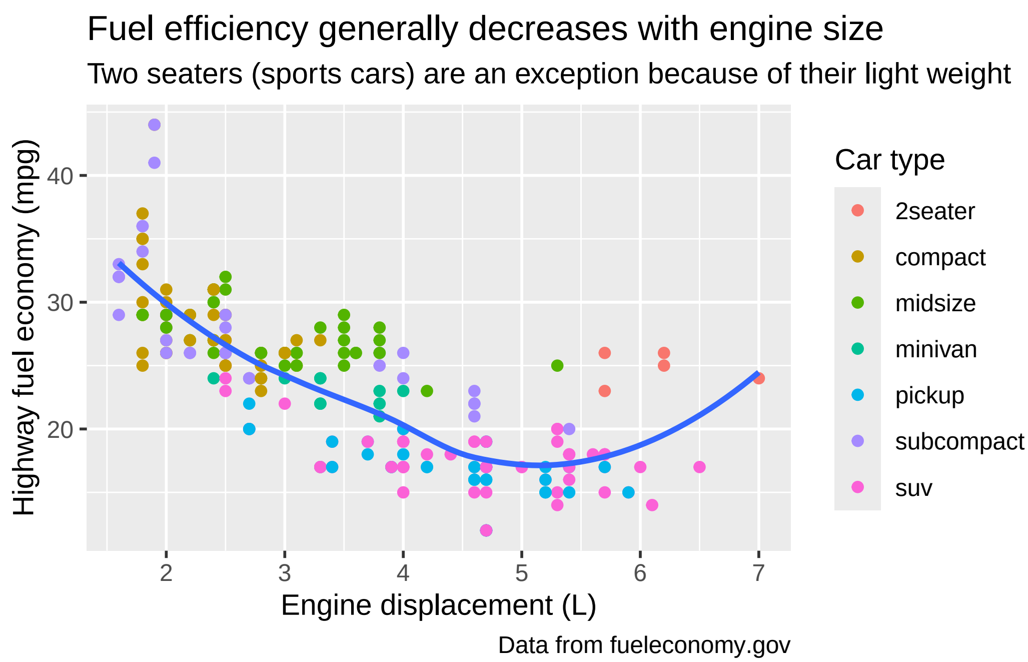
Annotations are introduced as tools for guiding interpretation, highlighting key patterns, or explaining anomalies. The chapter also discusses how consistent visual styling improves credibility and professionalism.

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
```

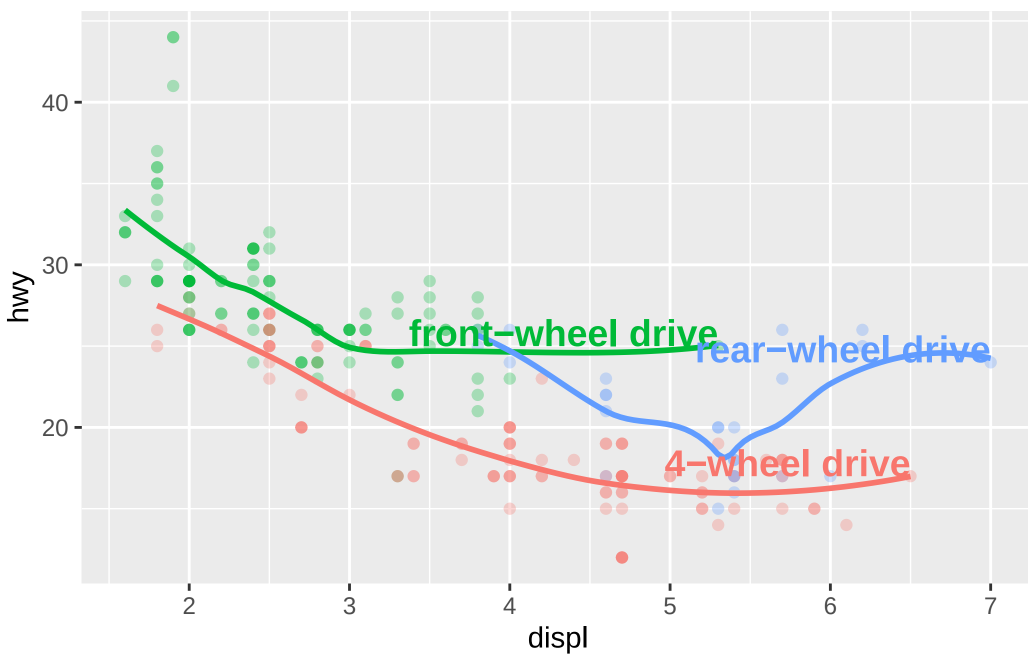
```
# A tibble: 3 x 4
# Groups:   drv [3]
  displ   hwy drv   drive_type
  <dbl> <int> <chr> <chr>
1   6.5    17 4     4-wheel drive
2   5.3    25 f     front-wheel drive
```

```
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

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

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

```
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

```
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

```
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.

Example 1

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

```
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
```

Example 2

```
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

```
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))
```