Cédric Scherer

Graphic Design with ggplot2

Create Beautiful and Engaging Data Visualizations in R

To my son,

without whom I should have finished this book two years earlier

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Preface

Back in 2016, I had to prepare my PhD introductory talk to inform about my plans for the next three years and to showcase my first preliminary results. I planned to create a visualization using small multiples to show various outcomes of the scenarios I ran with my simulation model. I was already using the R programming language for years and quickly came across the graphics library **ggplot2** which comes with the functionality to easily create small multiples. I never liked the syntax and style of base plots in R, so I immediately fell in love with the idea and implementation of **ggplot2**'s *Grammar of Graphics*. But because I was short on time, I plotted these figures by trial and error and with the help of lots of googling. The resource I came always back to was a blog entry called "Beautiful plotting in R: A **ggplot2** cheatsheet" by Zev Ross[1]. After giving the talk which contained some decent plots thanks to the blog post, I decided to go through this tutorial step-by-step. I learned so much from it and directly started modifying the codes and adding additional code snippets, chart types, and resources.

Fast forward to 2019. I successfully finished my PhD and started participating in a weekly data visualization challenge called #TidyTuesday[2]. Every week, a raw data set is shared with the aim to explore and visualize the data with **ggplot2**. Thanks to my experience with the **tidyverse** and especially **ggplot2** during my PhD and the open-source approach of the challenge that made it possible to learn from other participants, my visualizations quickly became more advanced and complex.

A few months later, I had built a portfolio of various charts and maps and decided to start working as an independent data visualization specialist. I am now using **ggplot2** every day: for my academic work, design requests, reproducible reports, educational purposes, and personal data visualization projects. What I especially love about my current job specification: It challenges and satisfies my creativity on different levels. Besides the creativity one can express in terms of chart choice and design, there is also creativity needed to come up with solutions and tricks to bring the most venturous ideas to life. At the same time, there is the gratification when your code works and *magically* translates code snippets to visuals.

The blog entry by Zev Ross was not updated since January 2016, so I decided to add more examples and tricks to my version, which was now hosted on my personal blog[3]. Step by step, my version became a unique tutorial that now contains for example also the fantastic **patchwork**, **ggtext** and **ggforce** packages, a section of custom fonts and colors, a collection of R packages tailored to create interactive charts, and several new chart types. The updated version now contains ~3.000 lines of code and 188 plots and received a lot of interest from **ggplot2** users from many different professional fields.

Today, on a sunny day in July 2021, this tutorial serves as the starting point for the book you hold in your hands. I hope you enjoy it as much as I enjoyed learning and sharing **ggplot2** wizardry!

[1] http://zevross.com/blog/2014/08/04/beautiful-plotting-in-r-a-ggplot2-cheatsheet-3/
[2] https://github.com/rfordatascience/tidytuesday/blob/master/README.md
[3] https://www.cedricscherer.com/2019/08/05/a-ggplot2-tutorial-for-beautiful-plotting-in-r/

Why read this book

Often, people that use common graphic design and charting tools or have basic experience with **ggplot2** cannot believe what one can achieve with this graphics library—and I want to show you how one can create a publication-ready graphic that goes beyond the traditional scientific scatter or box plot.

ggplot2 is already used by a large and diverse group of graduates, researchers, and analysts and the current rise of R and the tidyverse will likely lead to an even increasing interest in this great plotting library. While there are many tutorials on **ggplot2** tips and tricks provided by the R community, to my knowledge there is no book that specifically addresses the complete design of specific details up to building an ambitious multipanel graphic with **ggplot2**. As a blend of strong grounding in academic foundations of data visualization and hands-on, practical codes, and implementation material, the book can be used as introductory material as well as a reference for more experienced **ggplot2** practitioners.

The book is intended for students and professionals that are interested in learning **ggplot2** and/or taking their default ggplots to the next level. Thus, the book is potentially interesting for **ggplot2** novices and beginners, but hopefully also helpful and educational for proficient users.

Among other things, the book covers the following:

- Look-up resource for every-day and more specific ggplot adjustments and design options
- Practical hands-on introduction to **ggplot2** to quickly build appealing visualization
- Discussion of best practices in data visualization (e.g. color choice, direct labeling, chart type selection) along the way
- Coverage of useful **ggplot2** extension packages
- Ready-to-start code examples
- Reference implementations illustrating code solutions and design choices

How to read this book

This book can either serve as a textbook or as a reference. Depending on your skill level, some codes and tricks may already be known or not helpful at the moment. In case you want to directly jump to the chapters you find most promising or helpful, here are some suggestions:

- How do I get started with the code? → Chapter 3
- I have no idea how **ggplot2** actually works and need a quick introduction → Chapter 2.1

Prerequisites

To run any of the materials locally on your own machine, you will need the following:

- A recent version of R (download from here[4])
- Preferably an *Integrated Development Environment* (IDE) to store scripts and run code, e.g. RStudio (download from here[5]) or Visual Studio Code (download from here[6])
- A set of R packages installed:
  - **{tidyverse}**[7] that includes **{ggplot2}**[8]
  - **{ggforce}**[9]
  - **{ggrepel}**[10]
  - **{ggtext}**[11]
  - **{magick}**[12]
  - **{patchwork}**[13]
  - **{ragg}**[14]
  - **{rnaturalearth}**[15]
  - **{scico}**[16]
  - **{sf}**[17]

To install all packages in one go, run the following code in the R console:

```
install.packages(c(
  "tidyverse", "ggforce", "ggtext", "magick", "patchwork",
  "ragg", "rnaturalearth", "scico", "sf"
))
```

Software information and conventions

The book was written with the **{knitr}** package (Xie, 2015) and the **{bookdown}** package (Xie, 2022) with the following setup:

```
## R version 4.2.2 (2022-10-31)
## Platform: aarch64-apple-darwin20 (64-bit)
## Running under: macOS Ventura 13.0
##
## Locale: en_US.UTF-8 / en_US.UTF-8 / en_US.UTF-8 / C / en_US.UTF-8 / en_US.UTF-8
##
## Package version:
##   base64enc_0.1.3   bookdown_0.31
##   bslib_0.4.2       cachem_1.0.6
```

[4] https://cloud.r-project.org/
[5] https://rstudio.com/products/rstudio/download/#download
[6] https://code.visualstudio.com/download
[7] https://www.tidyverse.org/
[8] https://ggplot2.tidyverse.org/
[9] https://ggforce.data-imaginist.com/
[10] https://ggrepel.slowkow.com/
[11] https://wilkelab.org/ggtext/
[12] https://docs.ropensci.org/magick/
[13] https://patchwork.data-imaginist.com/
[14] https://ragg.r-lib.org/
[15] https://docs.ropensci.org/rnaturalearth/
[16] https://github.com/thomasp85/scico
[17] https://r-spatial.github.io/sf/

```
##   cli_3.5.0         compiler_4.2.2
##   cpp11_0.4.3       digest_0.6.31
##   ellipsis_0.3.2    evaluate_0.19
##   fastmap_1.1.0     fs_1.5.2
##   glue_1.6.2        graphics_4.2.2
##   grDevices_4.2.2   highr_0.10
##   htmltools_0.5.4   jquerylib_0.1.4
##   jsonlite_1.8.4    knitr_1.41
##   lifecycle_1.0.3   magrittr_2.0.3
##   memoise_2.0.1     methods_4.2.2
##   mime_0.12         R6_2.5.1
##   ragg_1.2.4        rappdirs_0.3.3
##   rlang_1.0.6       rmarkdown_2.19
##   rstudioapi_0.14   sass_0.4.4
##   stats_4.2.2       stringi_1.7.8
##   stringr_1.5.0     systemfonts_1.0.4
##   textshaping_0.3.6 tinytex_0.43
##   tools_4.2.2       utils_4.2.2
##   vctrs_0.5.1       xfun_0.36
##   yaml_2.3.6
```

Package names are in **bold text** and wrapped into curly brackets, e.g. **{ggplot2}**. Inline code and file names are formatted in a `monospaced typewriter font`. Function names are followed by parentheses as in `ggplot2::ggplot()`.

Acknowledgments

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About the Author

Dr Cédric Scherer[18] is a data visualization designer, consultant, and instructor helping clients and workshop participants to create engaging and effective graphics. As a graduated ecologist, he has acquired an extensive hypothesis–driven research experience and problem–solving expertise in data wrangling, statistical analysis, and model development. As an independent data visualization designer, Cédric later combined his expertise in analyzing large data sets with his passion for design, colors and typefaces.

Cédric has designed graphics across all disciplines, purposes, and styles applying a code–first approach and regularly talks about data visualization design and ggplot2 techniques. Due to participation in social data challenges such as #TidyTuesday, he is now well known for complex and visually appealing figures, entirely made with **{ggplot2}**, that look as if they have been created with a vector design tool. He also uses R and the **{tidyverse}** packages to automate data analyses and plot generation, following the code-first philosophy of a reproducible workflow.

[18] https://cedricscherer.com

1

Introduction

1.1 Communicating Data

Communicating data is critical for many of us, no matter if scientists, journalists, or analysts. How we present data affects the engagement of and interpretation by the audience. Showing data in an honest, meaningful—and maybe sometimes even playful or artistic—way is the art of ***data visualization*** or ***information visualization***. Data visualization can be described as the transformation of numbers into visual quantities, encoded by forms, positions, and colors. The transformation allows us to see patterns and trends in data and identify relationships between different variables. In the best case, a well-designed data visualization helps to amplify cognition, facilitate insights, discover, spark curiosity, explain, and make decisions.

Data visualizations, or broadly speaking ***information graphics***, are often classified as being either exploratory or explanatory. ***Exploratory graphics*** are generated to understand the data and search for the relevant information. ***Explanatory graphics*** aim to communicate the derived information between people (Koponen and Hildén, 2019). In contrast to exploratory graphics, the creation of engaging explanatory graphics involves not only the display of data but also requires many choices with regard to the storytelling and design.

When designing visualizations myself or looking at the work of others, the most important question to me is the ***purpose*** of the graphic. Without a clear understanding of the purpose, it is impossible to design an effective and engaging visualization. The same applies when evaluating a visualization: without the consideration of the purpose—the audience, the message, the mood—the designer had in mind when creating the visualization, the critique of design choices often becomes obsolete. A common assumption is that the single aim of data visualizations is to guide decisions. This might be true for business or scientific applications that aim for precision and accuracy by creating *pragmatic visualizations* (Kosara, 2007).

At the same time, it is ignorant to assume that efficiency and functionality are the main purpose of every visualization. Many of the great visualizations we have seen and that stick to our mind go beyond the precise, informative display of data[1]. They experiment with new approaches, use clever, unusual ways to tell stories or were designed simply to transport joy, curiosity or concern. In some cases, the design and visual novelty may even be the main focus with the aim to create a novel, artistic experience for the viewer. Such artworks are not necessarily created to maximize discovery or communication but to elicit emotions and can be termed ***affective graphics***[2].

As a *creator*, clearly defining the purpose of a visualization helps to make decisions about the

[1] However, I am not saying that these are the only ones that are great—there are definitely several magnificent pragmatic visualizations that come to my mind!

[2] Credit to the term "affective graphics" goes to Alberto Cairo, thank you for sharing your thoughts with me.

data, the chart type, and the design. As a *reader*, identifying the purpose helps rating the quality of the presentation. Some people like to think that there is a single best approach to visualize data: the one that has survived the test of time and is the most efficient to quantify information. Some believe that a chart has to be designed in a *neutral* way. I strongly disagree with both opinions, for multiple reasons. The most important: Every time we present the data, we make decisions; and it is not about *if* we make decisions but *which*. Chart types are not inherently 'right' or 'wrong' but might be more or less suitable for the purpose. Colors are associated with some emotional value—how could we pick one that has a neutral meaning, association or emotion for every person that might look at your visualization?

Even if we agree on the 'right' decisions—the best chart type and a neutral color encoding, likely some shades of grey—we still can't ensure that all people interpret it in the same way. People will always find their own message in graphs and the interpretation will likely differ based on individual differences through culture, attitude and mood.

A quote from Alberto Cairo that is close to my heart sums it up brilliantly:

> Visualizations can be designed and experienced in various ways, by people of various backgrounds, and in various circumstances. That's why reflecting on the purpose of a visualization is paramount before we design it—or before we critique it. (Cairo, 2021)

In the optimal case, the decisions made by the creator are based on some thoughtful consideration of the following:

- *data* — which information is meaningful and robust?
- *audience* — what do readers already know?
- *context* — how will the reader encounter the visualization?
- *story* — what is the main message of the visualization?
- *goal* — which chart type is suitable to transport the story?
- *design* — how can I facilitate engagement and understanding?

While some decisions might (and should) be made before crafting the visualization, the creation of purposeful, well-designed graphics is an iterative process. Rarely[3] the first draft is what ends up being printed on physical material or being displayed on your computer or smartphone screen. Nowadays, computational approaches ease the cyclic process of prototyping, exploring, testing, and designing the best visual encoding of information for a given purpose.

[3] I was very tempted to write "never" but I don't have data to support this claim…

1.2 Coding Visualizations

As data visualizations involve the quantitative representation of variables, an environment that allows to handle, wrangle and quantify data is preferential. Classical design software is great to create vector-based graphics of all kinds but must often be paired with a 'visualization tool' if the data and/or the chart type becomes more complex. While there are many tools that allow to quickly create specific, predefined chart types (e.g. DataWrapper, Flourish, RAWgraphs), often also with beautiful and very sensible defaults, such chart builders usually do not provide full flexibility.

By using a computational, code-driven approach we can combine all steps related to data visualization in the same environment: from the data import and cleaning to the precise and flexible encoding of quantitative information with custom designs. Programming languages such as JavaScript, Python, or R have a much steeper learning curve but at the same time allow users to create almost any visualization one can think of. Furthermore, they come with several *extension libraries* (e.g. D3.js, echarts, Vega, Matplotlib, ggplot2) that provide additional approaches or add more opportunities to existing code.

Data visualizations that are generated with code have several other benefits. The *reproducibility* of code makes the process more efficient by being able to update the data or to use the code as a template for future projects. The *transparency* of coded (and well-documented) data workflows increases trust. The *scalability* of code allows to produce the graphics for multiple data sets and use cases.

Of course, the visualization does not need to be created by code alone. Switching from a code-based approach to a vector-graphics tool makes a lot of sense in use cases where reproducibility does not matter or graphics are stand-alone artworks. Honestly, in terms of efficiency and freedom, a combined approach is likely the best approach in such a case.

With that in mind, knowing how to code visualizations is likely beneficial in any data-related field.

1.3 Why R and ggplot2

As a computational ecologist, I've learned and used a range of different tools and programming languages for various purposes such as data wrangling, statistical analyses, and model building. The open-source language R was and is the programming language most widely used by ecologists to handle and analyze ecological data (Sciaini et al., 2018). Consequently, I was *of course* using R in my daily life as an scientific researcher.

Nowadays, R plays a crucial part in many data-related workflows, no matter if for scientific, educational, or industrial use cases. Thanks to the ever growing R community and the rich collection of libraries that add additional functionality and simplify workflows, R is an attractive programming language that has outgrown of its original purpose: statistical analyses. Today, R can serve as tool to generate automated reports, develop stand-alone web apps, and draft presentation slides, books, and web pages. And to design high-level, publication–ready visualizations.

Even though R—similar to most programming languages—has a steep learning curve, the

level of functionality, flexibility, automation, and reproducibility offered can be a major benefit also in a design context:

- The layered approach of **ggplot2** opens the possibility to build any type of visualization.
- Various extension packages add missing functionality.
- Script-based workflows instead of *point–and–click* approaches allow for reproducibility—which means you can run the code again after receiving new data or create thousands of visualizations for various data sets in no time.
- Sharing code is becoming the golden standard in many fields and thus facilitates transparency and credibility as well as modification and creative advancement.
- A helpful community and many free resources simplify learning experiences and the search for solutions.
- The visualizations created in R can be exported as vector files and thus allow for post–processing with vector graphics software like Adobe Illustrator, Inkscape or Figma.

2

The Layered Grammar of Graphics

2.1 The {ggplot2} Package

In 2005 Hadley Wickham implemented Leland Wilkinson's "The Grammar of Graphics"[1] (Wilkinson, 2005)—a general concept for data visualization—as an R package called **{ggplot2}**[2] (Wickham, 2016). The idea of both, the theoretical concept and its implementation in **{ggplot2}**, is that data visualizations can be defined as semantic components rather than as predefined chart types. The ability to control and combine multiple components makes it a powerful approach to compose complex graphs, iterate quickly over different visual data representations, and modify existing plots. Furthermore, it allows for a comprehensive and consistent syntax to describe and build data visualizations.

The package was intially released on June 10, 2007 and has since then become one of the most popular R packages and the standard for producing custom, high-quality graphics in R. The predessor, the original **{ggplot}** package[3], was released in 2006 and is made available out of historical interest.

When looking into the package description of the **{ggplot2}** package[4], it states the following:

> **{ggplot2}** is a system for declaratively creating graphics, based on The Grammar of Graphics. You provide the data, tell **{ggplot2}** how to map variables to aesthetics, what graphical primitives to use, and it takes care of the details.

The most important insight from this technical description is that

1. we map variables to aesthetics, i.e. defining the visual channels used to represent the variables (e.g. position, color, shape)
2. we use graphical primitives, i.e. defininining one or multiple forms to represent the variables (e.g. lines, points, rectangles)

Both are important when writing **{ggplot2}** code and together with the provided data form the key components of a ggplot.

[1] https://link.springer.com/chapter/10.1007/978-3-642-21551-3_13
[2] https://ggplot2.tidyverse.org/
[3] https://github.com/hadley/ggplot1
[4] https://ggplot2.tidyverse.org/

2.2 The Components of a ggplot

In general, a ggplot is built up from the following components:

1. **Data**:
   The raw data that you want to plot.
2. **Aesthetics**:
   The mapping of variables to visual properties, such as position, color, size, shape, and transparency.
3. **Layers:**
   The representation of the data on the plot panel which is a combination of the *geometric shapes* representing the data and the *statistical transformation* of the data, such as fitted curves, counts, and data summaries.
4. **Scales**:
   The control of the mapping between the data and the aesthetic dimensions, such as data range to positional aesthetics or qualitative or quantitative values to colors.
5. **Coordinate system**:
   The transformation used for mapping data coordinates into the plane of the graphic.
6. **Facets**:
   The arrangement of the data into a grid of plots (also known as *trellis* or *lattice plot*, or simply *small multiples*).
7. **Visual themes**:
   The overall visual (non-data) details of a plot, such as background, grid lines, axes, typefaces, sizes, and colors.

The number of elements may vary depending on how you group them and whom you ask. This list is based on the list provided in the "ggplot2" book by Hadley Wickham[5] (Wickham, 2016).

A basic ggplot needs three key components that you have to specify: the *data*, *aesthetics*, and a *layer*. All other additional components can be further modified to customize your graphic.

You can think of a ggplot as a receipt for a dish: it can be based on a few or a diversity of ingredients. Also, you are free to add additional ingredients to spice-up your creation (literally and visually).

Similarly, you can build rather basic charts such as scatter plots or histograms with only a few lines code. But **{ggplot2}** also allows to create rather complex charts that combine multiple geometries, statistical transformations and maybe even data sets. On top, it is up to you how much effort you take to polish the plot. You can rely on the defaults used for data-related aesthetics (e.g. default axis breaks and color palettes) and non-data aspects (e.g. complete themes). Or you decide to modify the data-related aesthetics such as axes and color palettes and/or customize the theme elements of your graphic to your needs.

[5] https://ggplot2-book.org/introduction.html

2.3 Key Components

2.3.1 Data

Without data, there is no data visualization. Luckily, there are many sources of data available to us: statistics, surveys, experiments, and observations. The data may be collected by governments, researcher labs and organisations, companies—or yourself. However, it is important to consider the quality and context of the data you choose in order to gain accurate and valuable insights.

The ***quality*** of the data we use will have a direct impact on the validity and usefulness of the insights we gain from our data visualization. Poor quality data can lead to incorrect conclusions, while high quality data can provide valuable insights and help us make informed decisions.

In addition to the quality of the data, it is also important to consider the ***context*** in which the data was collected. Different data sources may have different biases or limitations, and it is important to consider these when interpreting and visualizing the data.

Usually, data visualization should be based on real data. At the same time, it is of course possible to create visualizations using hypothetical or simulated data to train yourself or experiment with new chart types. However, you should always keep in mind the origin of the data and communicate the fact clearly to your audience to avoid misleading insights. In order to truly understand and learn from data, we need to work with real, accurate, and reliable data.

Depending on how you want to display your data in **{ggplot2}**, you have to prepare the data in different formats. The general recommendation is to use a "long format" or "tidy format". In a tidy-form data set, each variable is stored in a column while rows form single observations (2.1). With such a data set, we can display each variable using a different visual channel, the *aesthetics*, such as position, color and shape (see 2.2 A). Consequently, data in true "long format" (i.e. the variable is specified in a dedicated row) is only useful in case you want to display the variables using the same visual channel (see 2.2 B). A wide format, as you might often find it in case of governmental data, often needs some reshaping except the goal is the representation of a single combination.

If you need to reshape your data, the `pivot_*()` functions from the **`{tidyr}`** package are handy. Use `pivot_longer()` to convert a wide data set into the long or tidy format. To go the other direction, use the `pivot_wider()`. You can find an example in chapter 3.2.5.2.

2.3.2 Aesthetics

To visualize certain variables in your data set with **{ggplot2}**, values are mapped to visual channels called *aesthetics*. Aesthetic attributes include positional information such as x and y but also colors, fills, point shapes, line types, sizes, and levels of transparency.

Sticking to our small data set, we could use our tidy-form data (2.1, top right) to create a scatter plot of the two metrics (2.2 A). However, we could also use the long-form data (2.1, top left) to show the metrics as a group wise dot plot and encode the metrics by shape(2.2 B).

The optimal shape of your data set relates to the plot you have in mind. Stick to the rule that any variable that you want to use for an aesthetic should have a dedicated column.

Long format:

– rows are single measurements
– all measurements are stored in a single column

group	year	metric	value
A	2022	x	46
B	2022	x	2
C	2022	x	21
A	2023	x	32
B	2023	x	16
C	2023	x	7
A	2022	y	12
B	2022	y	35
C	2022	y	24
A	2023	y	1
B	2023	y	42
C	2023	y	27

Tidy format:

– rows are observations, columns are variables
– all values are cell inputs

group	year	metric_x	metric_y
A	2022	10	32
B	2022	2	35
C	2022	13	10
A	2023	12	43
B	2023	16	42
C	2023	7	27

Wide format:

– variables and/or observations are spread across multiple columns
– some values are encoded in the column names

group	metric_x_22	metric_y_22	metric_x_23	metric_y_23
A	46	12	32	1
B	2	35	16	42
C	21	24	7	27

FIGURE 2.1: A comparison of data arranged in a long (left) versus wide formats (right). The two different metrics by color. Groups are additionally encoded by shaded rows.

2.3.3 Layers

Layers in **{ggplot2}** define the the statistical transformation, geometrical representation, and positional adjustment of the mapped values. In the example above, we have used a layer with geometry "point" and without any statistical transformation or positional adjustment. This specification simply means "draw the raw values as points by using the specified aesthetics of position, color, and shape".

Statistical transformation are responsible for calculating summaries such as counts and averages. You can also perform more advanced transformations of the data such as calculating smoothings and densities. If there is any statistical transformation specified, the calculation is applied to the data before they are plotted.

The raw or transformed data are then used to draw the specified geometrical object(s), representing the parsed data e.g. as points, bars, or lines. On top, you can also adjust the position of the geometries. Examples for positional adjustments are the grouping or stacking of bars or the jittering of points.

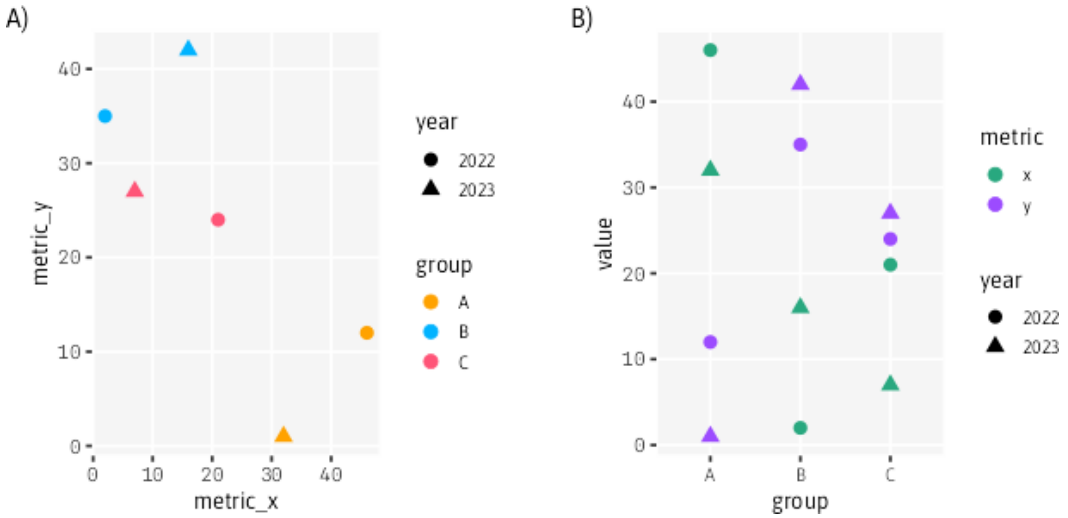


FIGURE 2.2: Basic ggplot outputs mapping four different variables (columns of the data set) to aesthetics, using the long-format data (`data_long`, left plot) and wide-format data (`data_wide`, right plot).

For example, you might use a statistical transformation to calculate linear regression lines to fit them to your variables mapped to x and y and display them as banded lines (geometrical object). Or you might decide to show the raw data as points without any statistical transformation (2.3).

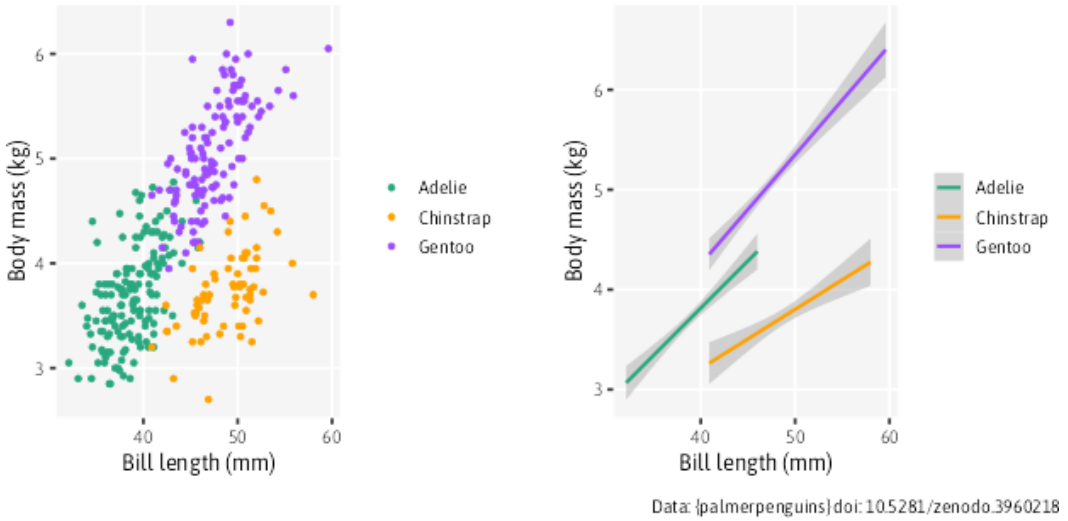


FIGURE 2.3: The same data, visualized as a scatter plot showing the raw data without any statistical transformation (left) and after a statistical tranformation has been applied to calculate linear fittings for each Penguin species (right). The visualizations use the Palmer Archipelago penguin data by A.M. Horst, A.P. Hill & K.B. Gorman (2020).

In general, each layer in a ggplot is created using a separate function call. For each layer, you can specify the visual appearance, such as color, and size, independently by *setting properties* (e.g. turn all points green) or *mapping aesthetics* (e.g. base the color on the

group variable). This allows you to build up a complex plot by adding and customizing individual layers, giving you fine-grained control over the appearance of your plots.

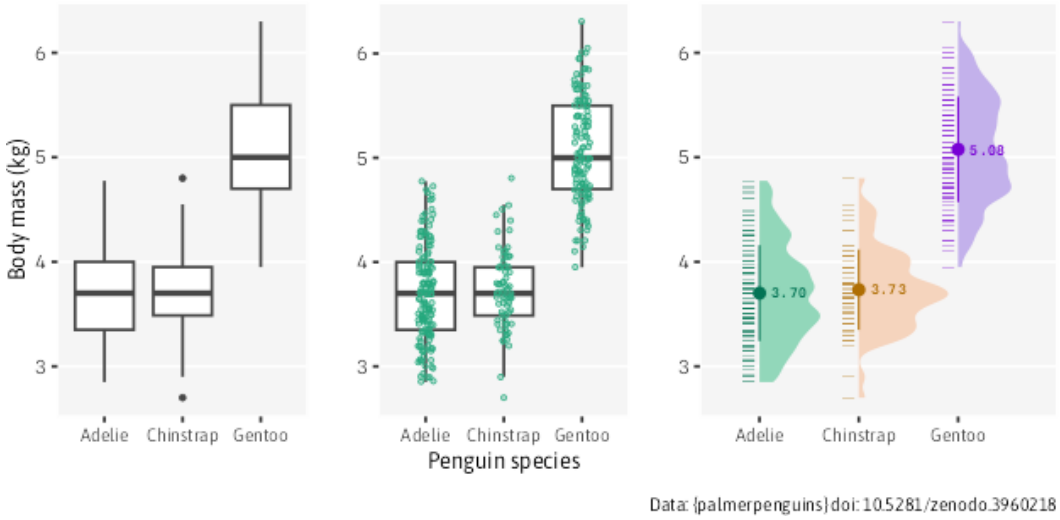


FIGURE 2.4: Three different visualizations showing the distribution of body mass across three penguin species. A) A box-and-whiskers plot using a single layer. B) Adding a second layer to plot A allows to show the raw data as jittered points. C) By combining multiple layers, one can build more complex visualizations like this variant of a raincloud plot. Four layers are used here: one for the density curve, one for the pointrange, another one for the barcode strip and finally one for the annotation with the mean values. The visualizations use the Palmer Archipelago penguin data by A.M. Horst, A.P. Hill & K.B. Gorman (2020).

The layered approach allows to create a wide range of charts and graphics. One can also create more complex, potentially unusual graphics as it allows you to combine layers in a traditional but also nontraditional way as you like.

2.4 Additional Components

The following components are set by default but can be tweaked to:

- adjust the properties of the aesthetics (scales)
- control the mapping of positional aesthetics (coordinate systems)
- create small multiples of the specified chart (facets)
- modify non-data related elements (themes)

2.4.1 Scales

Scales translate between the value range of our data, mapped to aesthetics, and the perceptual property range. Every time you map a column to an aesthetic, a respective suitable scale component is added to your plot.

To modify the default settings you can specify your own scale, for example tweak the number of axis ticks or customize the colors used to encode groups. Furthermore, scales are also

used to transform the data before it is processed by the layer. An example of transforming the values with a scale component is the display of the data in discrete bins.

2.4.2 Coordinate Systems

Coordinate systems interpret the position aesthetics. By default, a Cartesian coordinate system is used to encode the x and y aesthetics. As this is likely the most common type in data visualization, you might modify coordinate systems only in two cases: creating circular plots such as pie charts and circular barplots or when projecting spatial data.

2.4.3 Facets

Facets split variables to multiple panels, allowing to create the same visualization for several combinations. Such small multiples can be a powerful tool to show high-dimensional data, to explore big data sets, and to compare patterns across variables and groups.

A special case of facets are geo-referenced small multiples: a set of visualizations is laid out in a grid that represents the original topography. Such graphics can be easily created in **{ggplot2}** with the help of the `{geofacet}` extension package.

2.4.4 Themes

Themes encode all non-data elements of your plots such as the typeface, background colors, and titles and captions. **{ggplot2}** comes with a set of complete themes that can be added to your plot and further modified with high flexibility.

The modified themes can easily be turned into your own custom theme function which can be used as a component in the same way. Also, several extension packages such as `{ggthemes}`, `{hrbrthemes}` or `{tvthemes}` provide even more complete themes to change the look of your visualization.

The ability to use pre-coded themes is a great feature as it allows for a consistent and corporate style while saving time to write the same code over and over again.

2.5 Showcase

The following collection of graphics illustrate the power and versatility of **{ggplot2}**—and a range of extension packages—to create customized, partly uncommon or complex charts. All these charts are the outcome of 100% R code, making use of multiple layers and customized colors, fonts, and themes.

The visualization “Artists in the USA” shows the…[WIP]

In the “Not my Cup of Coffee” visualization, I combined seven layers to create an overview of coffee bean ratings by the Coffee Quality Institute per country. Two layers, a dot plot and an interval strip, are used to highlight the distribution. Two different triangles highlight minimum (red and empty) and median (black and filled) scores. Text layers indicate the scores next to the triangles as well as the respective country at the begin of each interval. [WIP]

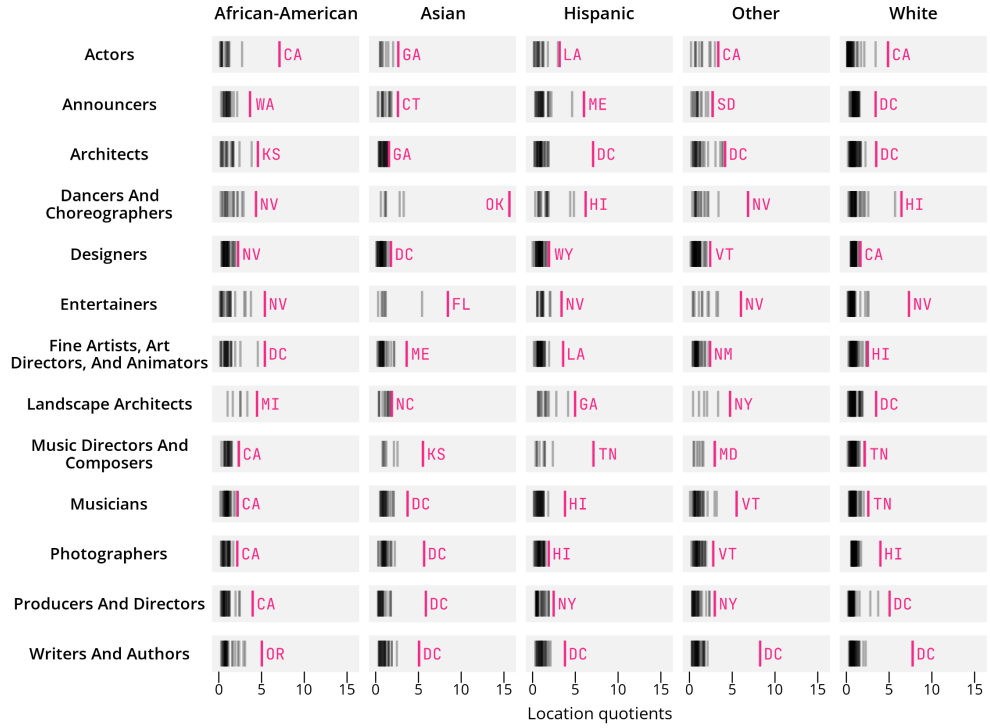


FIGURE 2.5: "Artists in the USA" by Lee Olney

Tanya Shapiro used a "jitter-pop" chart—a cmbination of jitter strips and lollipops—to visualize several average IMDb scores of the TV series "Doctor Who". Small jittered points show the average scores for each season, colored by doctor. The large circular images show visualize the average score per doctor with horizontal lines indicating the deviation from the overall average score (vertical line). This graphic combines five different layers: jittered points, images, text annotations, and horizontal and vertical lines. the package makes use of the extension packages … [WIP]

These are just a few examples of the many types of charts that you can create using **{ggplot2}**. With a little creativity and experimentation, you can come up with your own unique and informative visualizations or artful pieces.

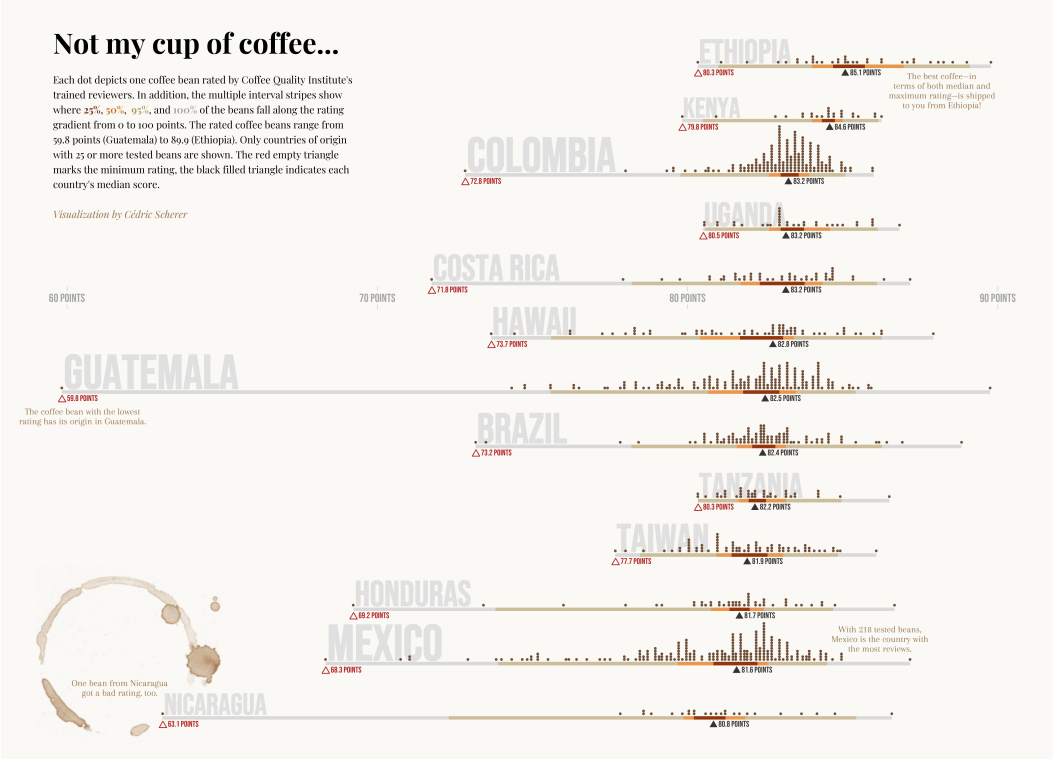


FIGURE 2.6: "Not my Cup of Coffee" by Cédric Scherer

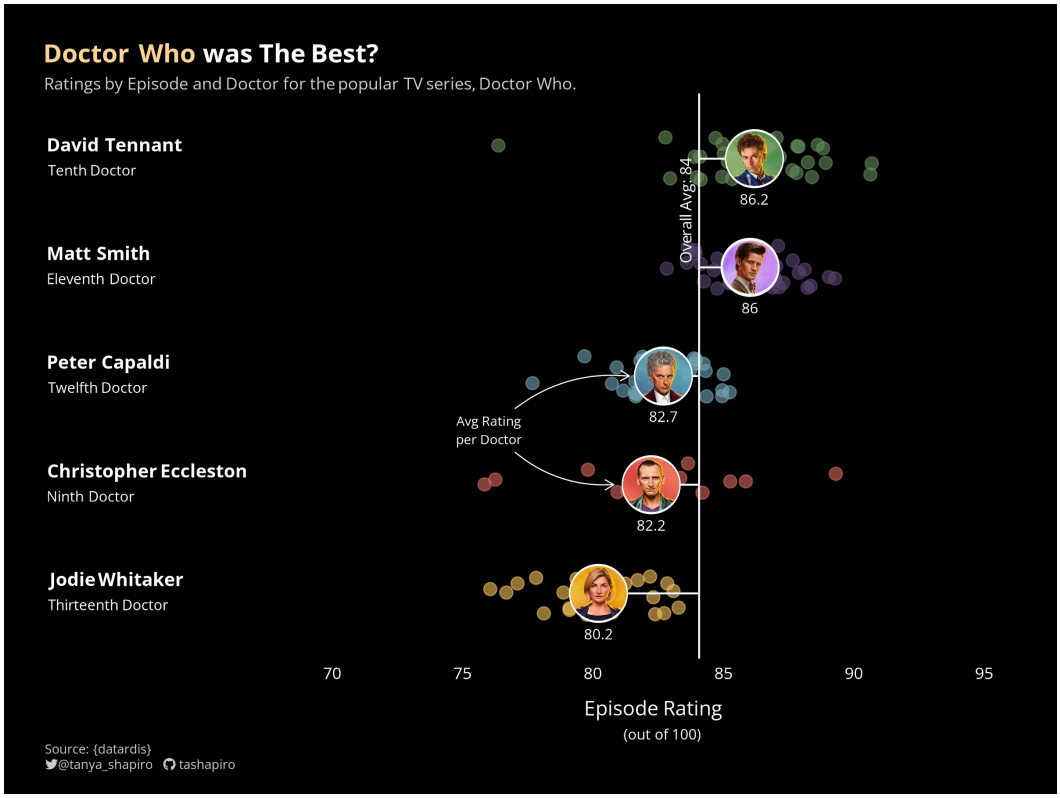


FIGURE 2.7: "Doctor Who was the Best?" by Tanya Shapiro

3

Get Started

3.1 The Data Set

We are using historical data for bike sharing in London in 2015 and 2016, provided by *TfL (Transport for London)*[1]. The data was collected from the TfL data base and is 'Powered by TfL Open Data'. The processed data set contains hourly information on the number of rented bikes and was combined with weather data acquired from freemeteo.com. The data was contributed to the Kaggle online community[2] by Hristo Mavrodiev.

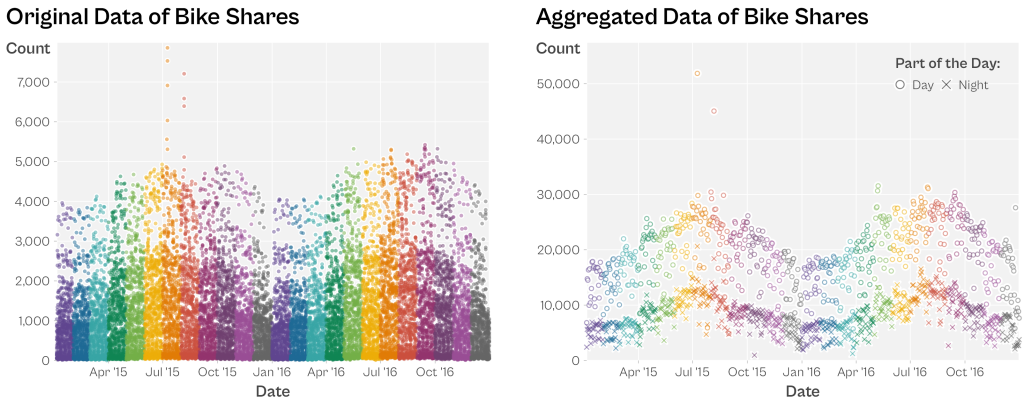


FIGURE 3.1: The original and aggregated data sets in direct comparison: counts of bike shares registered by TfL over time with month encoded by colour. The left panel shows counts for every hour of the day, while in the right panel the hourly data was aggregated into two periods of the day (day and night).

To make the visualizations manageable and patterns more insightful, we are using a modified data set with all variables aggregated for day (6:00am–5:59pm) and night (6:00pm–5:59am) (**??**). The bike counts were summarized while all weather-related variables where averaged. Finally, for the weather type, the most common was used and, in case of a tie, one of the most common types was randomly chosen. The modified data sets contains 14 variables (columns) with 1,454 observations (rows). To give you a better idea what the data set contains, a visual overview of the variables is provided in table **??** and figure **??**.

COMMENT: Decide on a version to provide and overview of the variables as table or list.

[1] https://tfl.gov.uk/modes/cycling/santander-cycles
[2] https://www.kaggle.com/hmavrodiev/london-bike-sharing-dataset

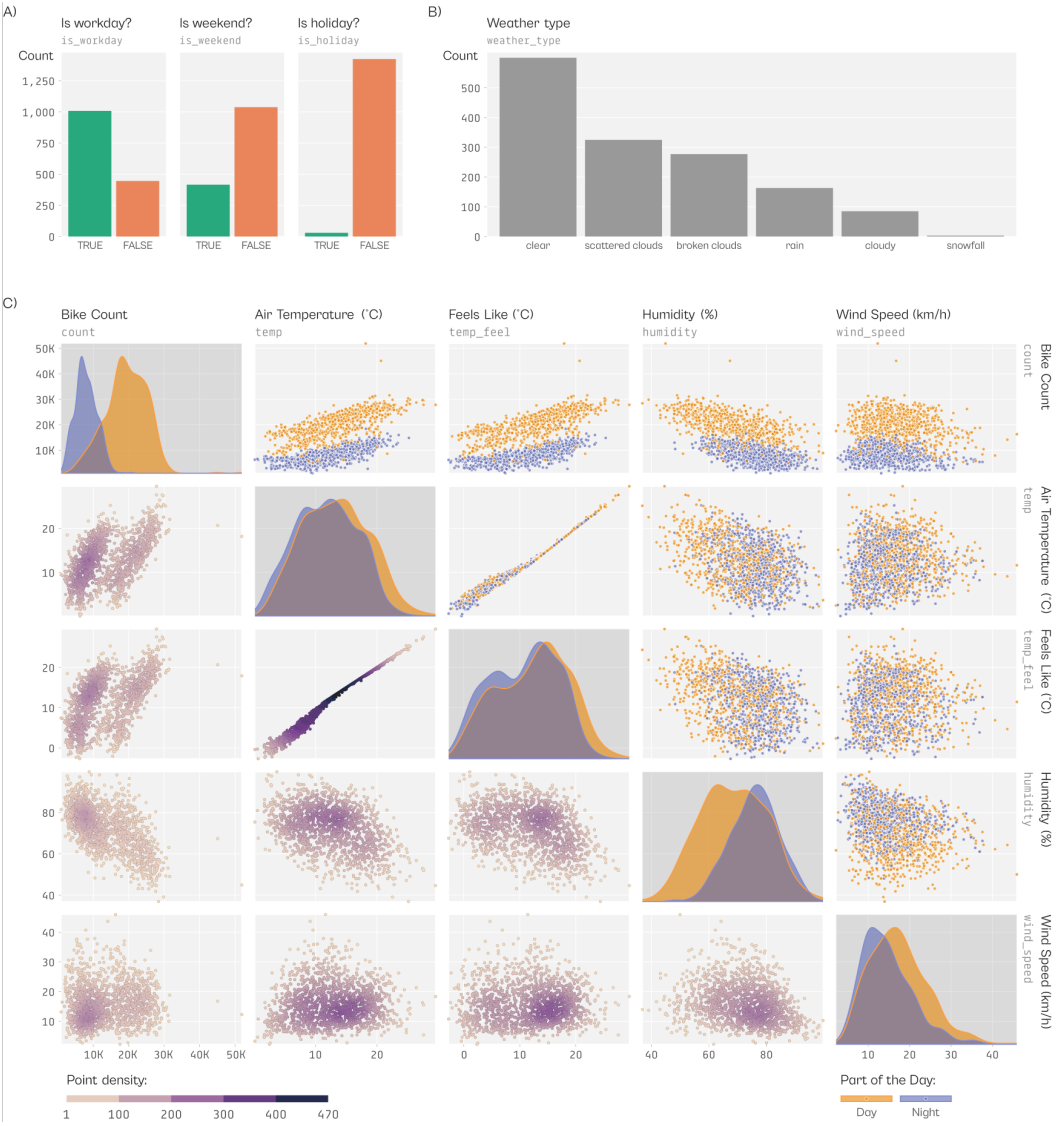


FIGURE 3.2: Overview of the distribution of the boolean variables `is_workday`, `is_weekend`, and `is_holiday` (A), the categorical variable `weather_type` (B), and the continuous variables `count`, `temp`, `temp_feel`, `humidity`, and `wind_speed` (C) of the cleaned and aggregated bike sharing data set. In panel C, the correlation between the variables is shown as scatterplot encoded by `timeperiod` (upper triangle) and encoded by point density (lower triangle), highlighting the level of overlap of data points.

TABLE 3.1: Overview of the 15 variables contained in the cleaned and aggregated bike sharing data set.

Variable	Description
‘date‘	Date encoded as ‘YYYY-MM-DD‘
‘day_night‘	‘day‘ (6:00am–5:59pm) or ‘night‘ (6:00pm–5:59am)
‘year‘	‘2015‘ or ‘2016‘
‘month‘	‘1‘ (January) to ‘12‘ (December)
‘season‘	‘0‘ (spring), ‘1‘ (summer), ‘2‘ (autumn) or ‘3‘ (winter)
‘count‘	Sum of bikes rented
‘is_workday‘	‘TRUE‘ being Monday to Friday and no official holiday
‘is_weekend‘	‘TRUE‘ being Saturday or Sunday
‘is_holiday‘	‘TRUE‘ being an official holiday in the UK
‘temp‘	Average air temperature (°C)
‘temp_feel‘	Average feels like temperature (°C)
‘humidity‘	Average air humidity (%)
‘wind_speed‘	Average wind speed (km/h)
‘weather_type‘	Most common weather typed

3.2 Working in R

{ggplot2} can be used even if you know little about the R programming language. However, the knowledge of certain basic principles is at least helpful and probably indispensable for advanced plots. This section will give you a short overview of workflows and the very basics needed. The overview makes use of the **{tidyverse}**, a package collection designed for data science in R. However, multiple other options exist to import, inspect, and wrangle your data if you prefer not to work with the **{tidyverse}** for these steps[3].

3.2.1 Import data

You need to import data to be able to work with it in the current session. The data can be imported from a local directory or directly from a web source. Nowadays, all common and some less common data formats can easily be imported. For common tabular data formats such as .txt or .csv one can use the **{readr}** package[4] (Wickham et al., 2022b) from the **{tidyverse}**.

We use the `read_csv()` function to load the TfL data as .csv file directly from a web URL. To access the URL and data later, we are storing the link as `url_data` and the data set as `bikes` by using the *assignment arrow* `<-`. The `col_types` argument within the `read_csv()` function allows to specify the column types. For example, `i` represents integer values, `f` encodes factors, and `l` turns a column into a logical, boolean variable that only can have two states, `TRUE` or `FALSE`. You’ll find more on the different *data types* later in this chapter.

[3] Note that the **{ggplot2}** package itself belongs to the **{tidyverse}** as well.
[4] https://readr.tidyverse.org/

```
url_data <- "https://cedricscherer.com/data/london-bikes.csv"
bikes <- readr::read_csv(file = url_data, col_types = "Dcfffillldddfc")
```

The `::` is called "namespace" and can be used to access a function without loading the package. Here, you could also run `library(readr)` first and `bikes <- read_csv(url_data)` afterwards.

If you want to load data that is stored locally, you specify the path to the file instead:

```
path_data <- "C://path/to/my/data/london-bikes.csv" ## mocked-up name for Win users
bikes <- readr::read_csv(file = path_data, col_types = "Dcfffillldddfc")
```

Note that the syntax of the path differs between operating systems. While in Windows subdirectories are separated with backslashes, Mac and Linux uses slashes. Also, absolute paths differ in their syntax: Windows machines specify the drive letter, here`C://`, or the server name; on Mac/Linux machines absolute paths start with `/users/`.

Instead of relying on the absolute path, which likely differs between users and operating systems, you can also use relative paths. Those are specified with a leading dot, e.g. as `./data/london-bikes.csv`, and look for the file relative from the working directory. You can retrieve and change your working directory with `getwd()` and `setwd()`. However, relying on the default working directory or setting a custom one will likely cause problems the moment someone else wants to run your code[5].

3.2.2 Project-oriented workflows

Preferably, we do not want to rely on absolute paths and the default or manually set working directories. So-called project-oriented workflows aim to organize each piece of work in a self-contained, bundled directory. This directory includes all relevant files needed for the project, such as scripts and images. By ensuring that paths are set relative and in a way that they are understood by any operating system, we guarantee that the project will run on any machine and can easily moved around.

If you are working in Rstudio, *Rstudio projects* provide such a project-oriented workflow. When opening the project via the associated `.Rproj` file, it ensures that the working directory is correctly set and points to the project's top-level directory (i.e. the folder that contains the `.Rproj` file).

When using Rstudio projects, a helpful package to navigate to files of interest is the **{here}** package[7]. The function `here()` will create paths relative to the top-level directory:

```
## point to the csv inside the "data" subdirectory of the project directory
path_data <- here::here("data", "london-bikes.csv")
```

[5] A detailed reasoning why you should not use `setwd()` is provided in Chapter 2 of "What they forgot you to teach about R"[6].

[7] https://here.r-lib.org/

3.2.3 Inspect data

After importing the data, it is advisable to have a look at the data. Does the object stored in R match the dimensions of your original data file? Are the variables displayed correctly? You can print the data by simply running the name of the object, here `bikes`.

```
bikes
```

```
## # A tibble: 1,454 x 14
##    date       day_ni~1 year  month season count is_wo~2
##    <date>     <chr>    <fct> <fct> <fct>  <int> <lgl>
##  1 2015-01-04 day      2015  1     3       6830 FALSE
##  2 2015-01-04 night    2015  1     3       2404 FALSE
##  3 2015-01-05 day      2015  1     3      14763 TRUE
##  4 2015-01-05 night    2015  1     3       5609 TRUE
##  5 2015-01-06 day      2015  1     3      14501 TRUE
##  6 2015-01-06 night    2015  1     3       6112 TRUE
##  7 2015-01-07 day      2015  1     3      16358 TRUE
##  8 2015-01-07 night    2015  1     3       4706 TRUE
##  9 2015-01-08 day      2015  1     3       9971 TRUE
## 10 2015-01-08 night    2015  1     3       5630 TRUE
## # ... with 1,444 more rows, 7 more variables:
## #   is_weekend <lgl>, is_holiday <lgl>, temp <dbl>,
## #   temp_feel <dbl>, humidity <dbl>, wind_speed <dbl>,
## #   weather_type <fct>, and abbreviated variable names
## #   1: day_night, 2: is_workday
```

As we have used the **{readr}** package, our data is stored as a *tibble* (class `tbl_df` and related) which is the **{tidyverse}** subclass of a traditional data frame (class `data.frame`). There are other data structures in R such as lists and matrices; however, in this book we are going to use only data frames, more precisely tibbles (besides spatial data formats in Chapter XYZ).

On the top of the output, you can directly see that our data set consists of `format(length(bikes), big.mark = ",")` variables (columns) frame with 1,454 observations (rows). Also, the tibble output shows you the first ten rows. Alternatively you can inspect the data with the help of `str()` or `tibble::glimpse()` to print a transposed version.

3.2.4 Data types

If you have looked carefully, you may have noticed that a tibble prints also the data type of each column, e.g. `<chr>`. In our case, we have specified the types of the columns manually when importing the data; if not specified, `readr::read_csv()` as most other import functions will guess the data type for each column based on the first x observations.

The data encoding is especially important when exploring chart options and writing ggplot code. You should be familiar if the data is encoded as quantitative or qualitative, if it contains missing or unusual values. Thus, it is always worth to check the classes and the values of the columns.

In R there are multiple low-level data types, and some of the **{ggplot2}** behavior will depend on the type of the variable(s) used for plotting. The six basic data types are:

- character
- factor
- numeric
- integer
- logical
- complex

To examine the data type of an object, use the `class()` function. The `$` symbol allows you to access single columns of a data frame, e.g. `bikes$day_night`:

```
class(bikes$day_night)
## [1] "character"

class(bikes$weather_type)
## [1] "factor"

class(bikes$temp)
## [1] "numeric"

class(bikes$count)
## [1] "integer"

class(bikes$is_weekend)
## [1] "logical"
```

Variables of type `character`, `factor`, and `logical` will be handled as **categorical, qualitative data** while `numeric`, `integer`, and `complex`[8] are treated as **numerical, quantitative data**.

The most important difference between the categorical types is their sorting: while `character` and also `logical` values are sorted alphabetically, `factor` variables have a specified order, defined by the so-called *levels*. Note that numbers can be treated as categorical as well and thus we can change their intrinsic order, too. We can inspect the order with the `levels()`:

```
levels(bikes$weather_type) ## an example of a factor with strings
## [1] "broken clouds"    "clear"
## [3] "cloudy"           "scattered clouds"
## [5] "rain"             "snowfall"

levels(bikes$season) ## an example of a factor with numbers
## [1] "3" "0" "1" "2"
```

Also, we can manually change the order of a factor by supplying a vector of level names to the `factor()` function:

```
bikes$season_mix <- factor(bikes$season, levels = c("2", "0", "3", "1"))
levels(bikes$season_mix)
## [1] "2" "0" "3" "1"
```

[8] As variables of type `complex` are rarely used in a data visualization context, we are going to ignore this data type.

The **{forcats}** package[9] (Wickham, 2022) provides a set of useful functions to reorder factor levels. Important functions to quickly change to order of variables include `fct_rev()`, `fct_reorder()`, `fct_infreq()`, `fct_inorder()`, and `fct_lump()`:

```
bikes$weather_type_rev <- forcats::fct_rev(bikes$weather_type)
levels(bikes$weather_type_rev)
## [1] "snowfall"         "rain"
## [3] "scattered clouds" "cloudy"
## [5] "clear"            "broken clouds"

bikes$weather_type_rank <- forcats::fct_infreq(bikes$weather_type)
levels(bikes$weather_type_rank)
## [1] "clear"            "scattered clouds"
## [3] "broken clouds"    "rain"
## [5] "cloudy"           "snowfall"
```

The single difference between the two numerical types `numeric` and `integer` is simply-speaking the existence of floating point numbers: while `numeric` variables store decimals, `integer` variables are stored as whole numbers. If you want to force integer values, you can specify them as `1L`.

```
head(bikes$temp) ## numeric
## [1] 2.167 2.792 8.958 7.125 9.000 6.708

as.integer(head(bikes$temp)) ## integer
## [1] 2 2 8 7 9 6
```

As shown in the last command, we can also convert data types. Be careful though, as R has internal rules how to *coerce* one data type into another. The same also happens if you specify a vector of multiple data types. In the following example, the `integer`, `numeric`, and `logical` values are coerced to `character` values. Afterwards, we explore the coercion behavior by converting the vector to other data types:

```
my_vector <- c(1L, 0.2, "ggplot", FALSE)
my_vector
## [1] "1"      "0.2"    "ggplot" "FALSE"

class(my_vector)
## [1] "character"

as.numeric(my_vector)
## [1] 1.0 0.2  NA  NA

as.integer(my_vector)
## [1]  1  0 NA NA

as.factor(my_vector)
```

[9] https://forcats.tidyverse.org/

```
## [1] 1      0.2    ggplot FALSE
## Levels: 0.2 1 FALSE ggplot

as.logical(my_vector)
## [1]    NA    NA    NA FALSE
```

When changing the data type of our `character` vector, some values are successfully converted (e.g. `1L` and `0.2` as `numeric` or `FALSE` as `logical`) while some are "wrongly" interpreted (e.g. `0.2` is converted into `0L` as `integer` or `FALSE` into `"FALSE"` as `character`). Some others are stored as `NA` representing *unknown, not available values* (e.g. `"ggplot"` as `numeric` or `1` as `logical`). Conversion between different data types is very useful but be careful and always inspect the output of the conversion for potential coercion mistakes.

Another important data type is the `Date` class. Dates are either represented as the number of days since a specified origin or converted `character` type with a structure of YYYY-MM-DD:

```
class(bikes$date)
## [1] "Date"

as.Date(1, origin = "1970-01-01")
## [1] "1970-01-02"

as.Date("2007-06-10")
## [1] "2007-06-10"

as.Date("2022-09-16") - as.Date("2007-06-10")
## Time difference of 5577 days
```

Furthermore, `POSIXct` and `POSIXlt` are able to represent full time stamps including a date and time. The two POSIX date/time classes only differ in the way that the values are stored internally.

```
as.POSIXct("2007-06-10 12:34:56")
## [1] "2007-06-10 12:34:56 CEST"

as.POSIXlt("2007-06-10 12:34:56")
## [1] "2007-06-10 12:34:56 CEST"
```

3.2.5 Data preparation

Often, the data imported might not be in the right format to plot it with **{ggplot2}**. The preparation of the data—e.g. converting data types and setting factor levels, aggregating values, estimating data summaries, reshaping the data set or combining it with another source—is called *data wrangling*, *data munging*, or **data manipulation**.

To explore and retrieve summary estimates of individual variables, the following functions are useful:

- `min()`, `max()`, `range()` to extract extremes of numerical data

- `quantile()` to get an idea of the distribution numerical data
- `unique()` to get all unique entries, helpful for categorical data
- `length(unique())` to count all unique entries

```
min(bikes$temp) ## add na.rm = TRUE in case it returns `NA`
## [1] 0.125

range(bikes$date)
## [1] "2015-01-04" "2016-12-31"

quantile(bikes$count)
##    0%   25%   50%   75%  100%
##   953  7508 11965 19412 51870

unique(bikes$day_night)
## [1] "day"   "night"

length(unique(bikes$weather_type))
## [1] 6
```

The **{dplyr}**[10] (Wickham et al., 2022a) and other **{tidyverse}** packages provide a simple and intuitive syntax to wrangle data. There are a ton of unique functions, but knowing a handful is enough to empower you to bring your data in the right format.

3.2.5.1 Data wrangling with the {dplyr} package

There are five main functions of **{dplyr}**, called *verbs*:

- `filter()`: Pick rows with matching criteria
- `select()`: Pick columns with matching criteria
- `arrange()`: Reorder rows
- `mutate()`: Create new variables
- `summarize()` or `summarise()`: Sum up variables

All of these functions follow a consistent syntax: `verb(data, condition)`. Note that we specify the data and columns individually and that within the tidyverse, column names are referred to without quotation marks:

```
## only keep more than 1000 shares during the night
filter(bikes, day_night == "night", count > 1000)

## only keep 4 columns and reorder those
select(bikes, date, count, weather_type, temp)

## order by day_night and decreasing bike shares
arrange(bikes, day_night, -count)

## add a column with temperature encoded as °F
mutate(bikes, temp_fahrenheit = temp * 1.8 + 32)
```

[10] https://dplyr.tidyverse.org/

```
## calculate the mean count across all observations
summarize(bikes, count_avg = mean(count))
```

Another important and very powerful function from the **{dplyr}** package is `group_by()`: when a data set is grouped into subsets, we can apply any operation for each group *within a single data frame*. While you could nest those functions, the common approach within the tidyverse is the use of *pipes*. Pipes take the output of one function and send it directly to the next which avoids nested operations and allows for a more logical order of functions and their arguments. The **{tidyverse}** pipe is encoded as `%>%`; a base R pipe is available as `|>` as well. Have a look at the following silly example:

```
## nested functions, read inside out + disconnected function inputs
go_to_work(
  breakfast(
    wake_up(
      Cedric, alarm = "06:30")
    ),
    c("coffee", "croissant")
  ),
  mode = "bus", delay = 10
)

## piped version with "Cedric" passed to the next function call
Cedric %>%
  wake_up(alarm = "06:30")) %>%
  breakfast(c("coffee", "croissant") %>%
  go_to_work(mode = "bus", delay = 10)
```

Let's create the workflow for some serious data preparation: In a first step, we are going to estimate the average temperature for night rents per year and season:

```
bikes_summarized <-
  bikes %>%
  ## only keep night observations
  filter(day_night == "night") %>%
  ## create 8 subsets (4 seasons x 2 years)
  group_by(season, year) %>%
  ## calculate total counts and mean temperature per subgroup
  summarize(
    count = sum(count),
    temp_avg = mean(temp)
  )

bikes_summarized
```

```
## # A tibble: 8 x 4
## # Groups:   season [4]
##   season year    count temp_avg
##   <fct>  <fct>   <int>    <dbl>
```

```
## 1 3      2015   459469     7.65
## 2 3      2016   489136     6.91
## 3 0      2015   693703     9.93
## 4 0      2016   676427     9.43
## 5 1      2015  1020524    17.2
## 6 1      2016  1044592    17.7
## 7 2      2015   685534    12.4
## 8 2      2016   744827    12.3
```

After filtering out "day" cases, the grouping by `season` and `year` allows us to summarize counts and average temperatures for each of the eight groups. Note that the resulting tibble is still grouped by `season` (as shown in the output with the `[4]` explicitly stating the number of current subsets).

In a next step, we regroup our data to add a column with shares of nightly bike rents per season on a yearly basis. Afterwards, we remove all subsets by calling `ungroup()` and clean our data set by reordering and removing columns and sorting rows by year and season:

```
bikes_summarized %>%
  ## add column with relative shares per year
  group_by(year) %>%
  mutate(share_year = count / sum(count)) %>%
  ## remove grouping
  ungroup() %>%
  ## reorder columns and remove days column
  select(year, season, count, share_year, temp_avg) %>%
  ## sort by year and season
  arrange(year, season)
```

```
## # A tibble: 8 x 5
##   year  season   count share_year temp_avg
##   <fct> <fct>    <int>      <dbl>    <dbl>
## 1 2015  3       459469      0.161     7.65
## 2 2015  0       693703      0.243     9.93
## 3 2015  1      1020524      0.357    17.2
## 4 2015  2       685534      0.240    12.4
## 5 2016  3       489136      0.166     6.91
## 6 2016  0       676427      0.229     9.43
## 7 2016  1      1044592      0.354    17.7
## 8 2016  2       744827      0.252    12.3
```

3.2.5.2 Reshaping data with the {tidyr} package

In case you need to reshape a data set to make it work with **{ggplot2}**, you can use the functions `pivot_longer()` and `pivot_wider()` from the **`{tidyr}`** package[11] (Wickham and Girlich, 2022) to move from one format to the other. Let's illustrate their behavior using one of the toy data sets used in section

[11] https://tidyr.tidyverse.org/

```
## create long-format data as showcased in section 2
data_long <- tibble::tibble(
  group = rep(c("A", "B", "C"), 4),
  year = rep(rep(c("2022", "2023"), each = 3), 2),
  metric = c(rep("x", 6), rep("y", 6)),
  value = c(46, 2, 21, 32, 16, 7, 12, 35, 24, 1, 42, 27)
)

## print long-format data
head(data_long, 5)
```

```
## # A tibble: 5 x 4
##   group year  metric value
##   <chr> <chr> <chr>  <dbl>
## 1 A     2022  x         46
## 2 B     2022  x          2
## 3 C     2022  x         21
## 4 A     2023  x         32
## 5 B     2023  x         16
```

```
## turn long-format data into wide-format data
data_wide <- tidyr::pivot_wider(
  data = data_long,        ## the long data set
  names_from = metric,     ## new column names
  values_from = value,     ## values to be filled in
  names_prefix = "metric_" ## adjust new column names
)

## print wide-format data
data_wide
```

```
## # A tibble: 6 x 4
##   group year  metric_x metric_y
##   <chr> <chr>    <dbl>    <dbl>
## 1 A     2022        46       12
## 2 B     2022         2       35
## 3 C     2022        21       24
## 4 A     2023        32        1
## 5 B     2023        16       42
## 6 C     2023         7       27
```

```
## turn wide-format data back to long-format data
data_long_again <- tidyr::pivot_longer(
  data = data_wide,             ## the wide data set
  cols = c(metric_x, metric_y), ## columns to pivot
  names_to = "metric",          ## column to hold variable
  values_to = "value",          ## column to hold values
  names_prefix = "metric_"      ## adjust new variable names
)
```

[WIP] lubridate, stringr, ...

4

A Walk-through Example

To illustrate the utility and flexibility of **{ggplot2}** to create complex, well-designed visualizations with a handful of components, we are going to create a set of four plots. For each combination of year and time of the day, we draw a scatter plot of bike rents including a linear fitting to show overall trends with feels-like temperature.

The creation of the plot itself will require only four lines of code! One to specify the data and global aesthetics, two for the scatter and fitting, and another one to create small multiples.

With a few more lines of code, we will adjust the labels, add annotations, and apply a custom color palette. Finally, we apply a personalized theme using custom typefaces.

4.1 Prerequisites

Before we can create a ggplot, we have to load the package by running `library(ggplot2)`. Also, we need import the data set we want to visualize, here our bike share data introduced in Section 3.1 which we store in an object called `bikes`.

```
## load the ggplot2 package
library(ggplot2)

## import bikes data set
url_data <- "https://cedricscherer.com/data/london-bikes.csv"
bikes <- readr::read_csv(file = url_data, col_types = "Dcfffillddddfc")
```

4.2 Create a basic ggplot

Once the **{ggplot2}** package is loaded, we can create a basic ggplot by specifying the *data*, *aesthetics*—the positional encoding of the variables—, and a *geometry*.

Here, we map the variable `temp_feel` of our `bikes` data object to the `x` position and the variable `count` to the `y` position (4.1). We will also map variables to all kind of other aesthetics throughout the book. Some are related to positions such as `xstart` and `ymax` while others change the appearance of the layer based on the variables they are mapped to such as `color` and `shape`.

There are many, many different geometries (often called geoms because each function starts

with `geom_`) one can add to a ggplot by default and even more provided by extension packages. By adding `geom_point()` we create a scatter plot:

```
ggplot(data = bikes) + ## initial call + data
  aes(x = temp_feel, y = count) + ## aesthetics
  geom_point() ## geometric layer
```

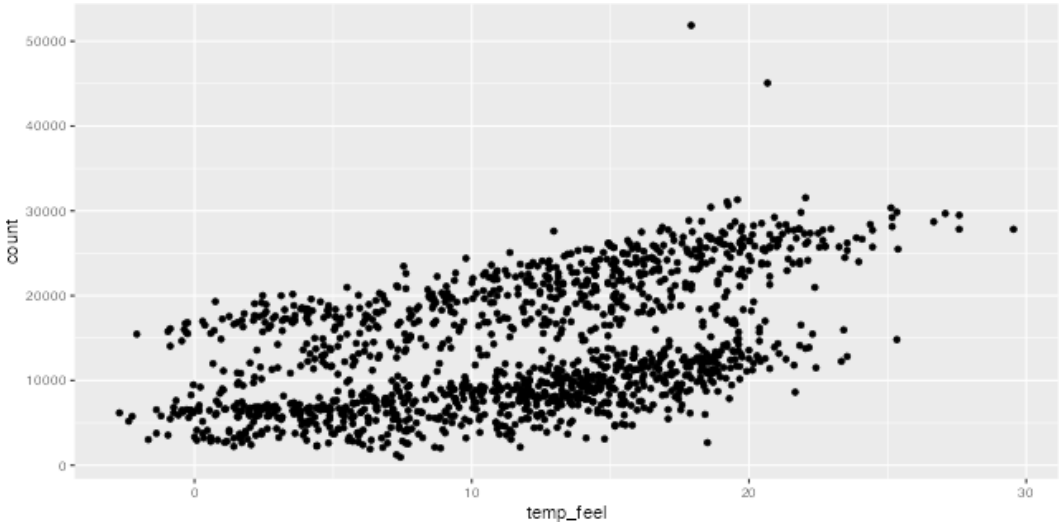


FIGURE 4.1: A basic scatter plot of feels-like temperature and reported TfL bike rents, created with the {ggplot2} package.

In most cases, you will find ggplot code in which the aesthetics are supplied inside the `ggplot()` call; however, both versions are valid.

```
ggplot(data = bikes, mapping = aes(x = temp_feel, y = count)) +
  geom_point()
```

Due to so-called *implicit matching*, we can rewrite the first part as `ggplot(bikes, aes(date, count))`, omitting the argument names `data` and `mapping` in the `ggplot()` call and `x` and `y` in the `aes()` function. This works as long as we respect the defined order.

Omitting the arguments `data` and `mapping` saves you a ton of typing when creating dozens to hundreds ggplots per day. In my opinion, it is good practice to refer to aesthetics explicitly, and I will follow this convention throughout the book.

4.3 Combine multiple layers

One can also add several layers, specified as either geometric shapes starting with `geom*()` or statistical transformations starting with `stat_*()` (4.2)—and this is where the magic and fun starts!

```
ggplot(bikes, aes(x = temp_feel, y = count)) +
  geom_point() +
  ## add a GAM smoothing
  stat_smooth()
```

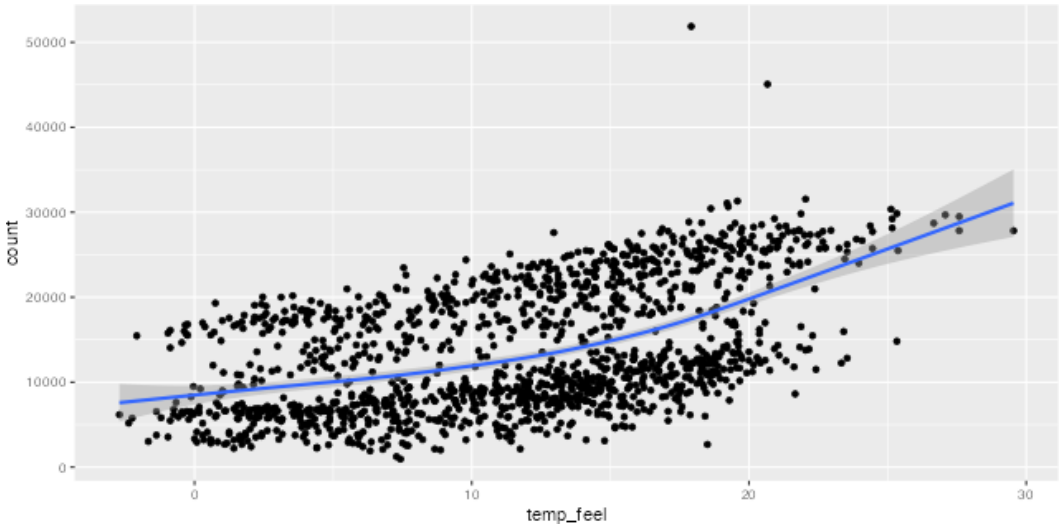


FIGURE 4.2: The same scatter plot, now with an additional GAM smoothing.

Both `geom_*()` and `stat_*()` internally make use of the same function `layer()` and pass default inputs for the `geom`, `stat`, and `position` arguments. Basically the use of geoms versus stats is only the perspective and personal preference: when specifying `geom_*()` we focus on the shape representing the variables; using `stat_*()` highlights the transformation applied to the variables. More information on the different geometries is provided in Chapter XYZ and a deep-dive into the power of statistical transformation is Chapter XYZ.

4.4 Mapping aesthetics in layers

By looking at these scatter plots, we can actually identify two different trends for day and night. We can highlight both groups by mapping the `day_night` variable to `color` (Fig. 4.3). Note that the mapping is applied to both, `geom_point()` and `geom_smooth()` and consequently the latter layer creates two separate smoothings.

```
ggplot(bikes, aes(x = temp_feel, y = count, color = day_night)) +
  geom_point() +
  stat_smooth()
```

Aesthetics can also be defined for each layer and are then applied locally to the respective geometry or statistical transformation only. The `group` aesthetics allows to create subsets without changing the visual appearance (in contrast to aesthetics such as `color` or `shape`).

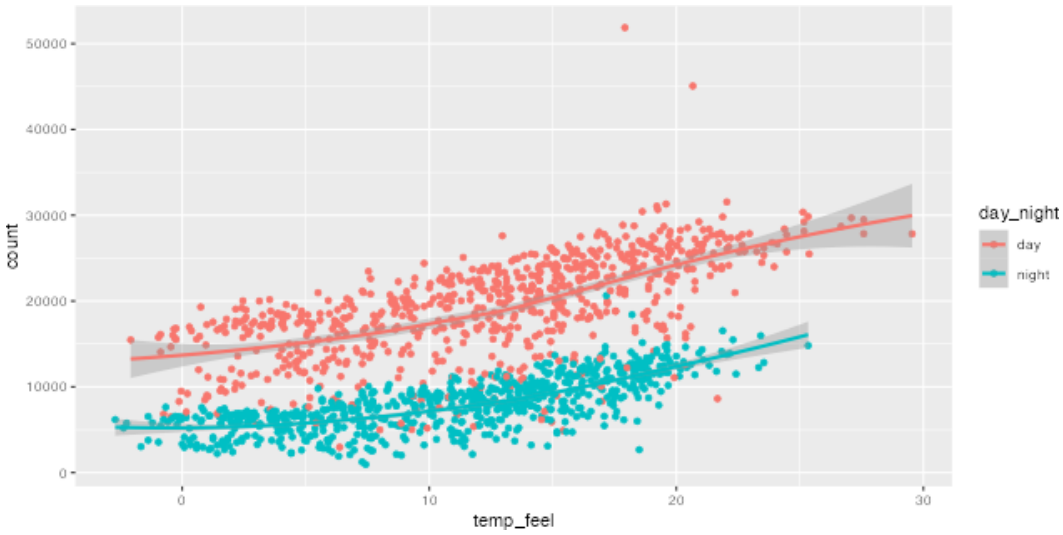


FIGURE 4.3: The points and smoothing lines colored by the time of the day.

You will learn more how to work with global and local aesthetics in Chapter XYZ and how to modify their appearance in Chapter XYZ.

4.5 Setting properties in layers

Furthermore, each layer has its own arguments to change their behavior and appearance. Let's also add some transparency to the points and turn the smoothing into a linear fitting (Fig. 4.4). As we are not mapping aesthetics but setting properties, we have to place those adjustments outside the `aes()` call.

```
ggplot(bikes, aes(x = temp_feel, y = count)) +
  geom_point(
    ## color mapping only applied to points
    aes(color = day_night),
    ## setting larger points with 50% opacity
    alpha = .5, size = 2
  ) +
  stat_smooth(
    ## invisible grouping to create two trend lines
    aes(group = day_night),
    ## use linear fitting + black smoothing lines
    method = "lm", color = "black"
  )
```

In general follow the rule to set constant properties outside `aes()` and map variables to aesthetics inside `aes()`.

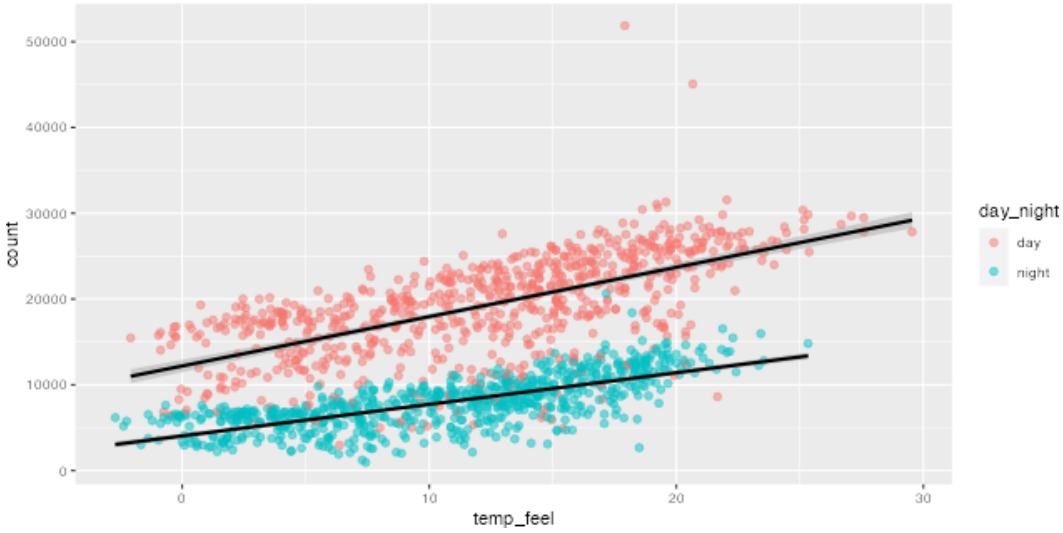


FIGURE 4.4: We can map aesthetics and define properties for each layer individually.

The different aesthetics and the differences of global versus local mapping of aesthetics is explained in Chapter XYZ.

4.6 Create small multiples

A fantastic feature of **{ggplot2}** is it's ability to quickly split a single visualization in a set of so-called *small multiples*: the same visualization, no matter how complex it is, is applied to subsets contained in the same data set. In **{ggplot2}**, such small multiples are called *facets* wich are conditional on the variables defined in the `facet_*()` function (Fig. 4.5).

```
ggplot(bikes, aes(x = temp_feel, y = count)) +
  geom_point(aes(
    color = day_night), alpha = .5, size = 2
  ) +
  stat_smooth(
    aes(group = day_night), method = "lm", color = "black"
  ) +
  ## small multiples based on time of the day (rows) and year (columns)
  facet_grid(day_night ~ year)
```

Consistency across axes is considered good practice as varying axis ranges are harder to compare and the potential of misleading viewers increases in case the differences keep unnoticed—or even worse are not noticeable. The implementation of facet in **{ggplot2}** ensures consistency across all small multiples by default, as illustrated by the empty space in the lower row as there are no values above ~21,000 reported rents during night.

The `facet` functionality also comes with the option to overwrite the default behavior by "freeing" the positional scales. Furthermore, one can ensure equal axis spacing by freeing

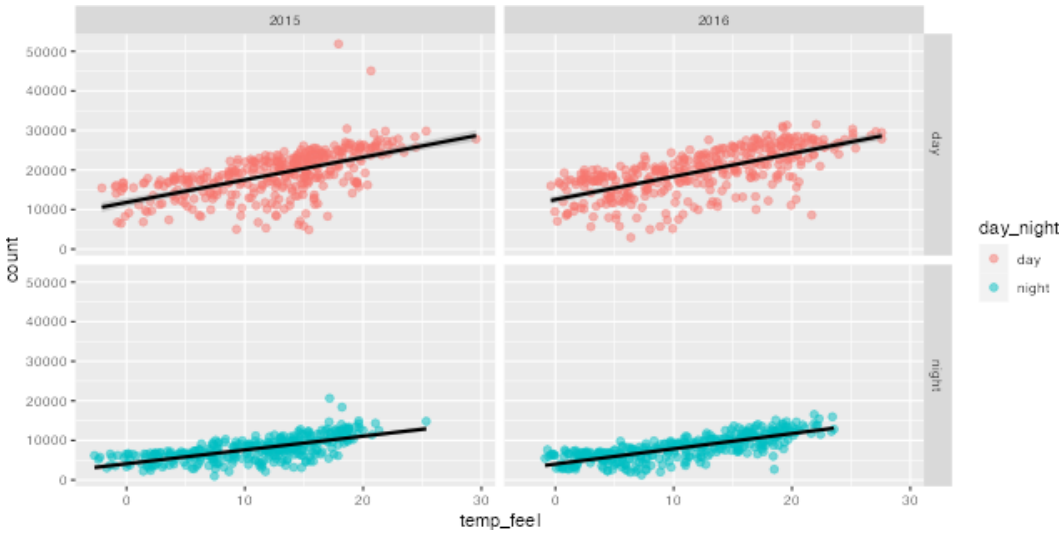


FIGURE 4.5: With the `facet` functions, a visualization can quickly be split into small multiples.

the space as well (Fig. 4.6). This setting allows to efficiently use the available space while ensuring comparability across plots and decreasing the potential of misleading the viewer. The differences between the two ways to create small multiples, namely `facet_grid()` and `facet_wrap()`, as well as ways to adjust and annotate facets are explained in Chapter XYZ.

```
ggplot(bikes, aes(x = temp_feel, y = count)) +
  geom_point(
    aes(color = day_night), alpha = .5, size = 2
  ) +
  stat_smooth(
    aes(group = day_night), method = "lm", color = "black"
  ) +
  facet_grid(
    ## free y axis range + scale heights respectively
    day_night ~ year, scales = "free_y", space = "free_y"
  )
```

4.7 Change the axis scaling

For every aesthetic, **{ggplot2}** applies so-called *scales* that translate between variable ranges (data) and property ranges (aesthetic). For the positional axes, a set of `scale_x_*()` and `scale_y_*()` controls their behavior. The `breaks` argument defines the placement of the axes ticks while the `labels` argument controls the labels next to those ticks. The labels can be either overwritten by a vector of the same length as the breaks (as for x in our example) or a function that returns a vector based on the breaks (as for y in our example). There are many more arguments such as `expand` to control the padding towards the ends of the

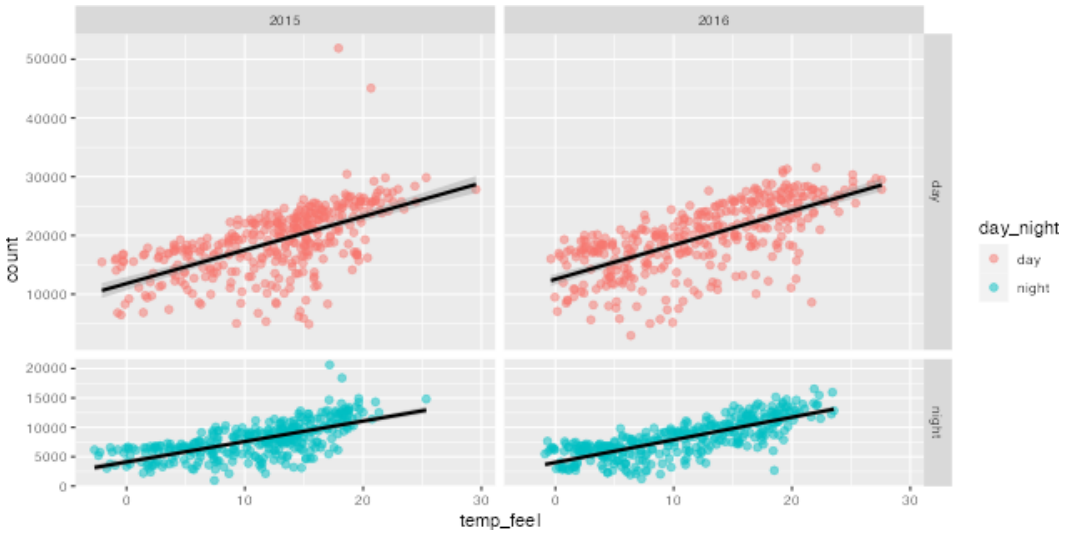


FIGURE 4.6: {ggplot2} even allows to free the axis range—while ensuring equal axis spacing.

respective axis or `trans` to transform the scale. You can read more about how to control `scales` in Chapter XYZ and about label adjustment and styling in Chapter XYZ.

```
ggplot(bikes, aes(x = temp_feel, y = count)) +
  geom_point(
    aes(color = season), alpha = .5, size = 2
  ) +
  stat_smooth(
    aes(group = day_night), method = "lm", color = "black"
  ) +
  facet_grid(
    day_night ~ year, scales = "free_y", space = "free_y"
  ) +
  ## x axis: add °C symbol + 5°C spacing
  scale_x_continuous(
    breaks = -1:6*5, labels = function(x) paste0(x, "°C"), expand = c(mult = 0, add = 1)
  ) +
  ## y axis: add a thousand separator + consistent spacing across rows
  scale_y_continuous(
    breaks = 0:5*10000, labels = scales::label_comma(), expand = c(mult = .1, add = 0)
  )
```

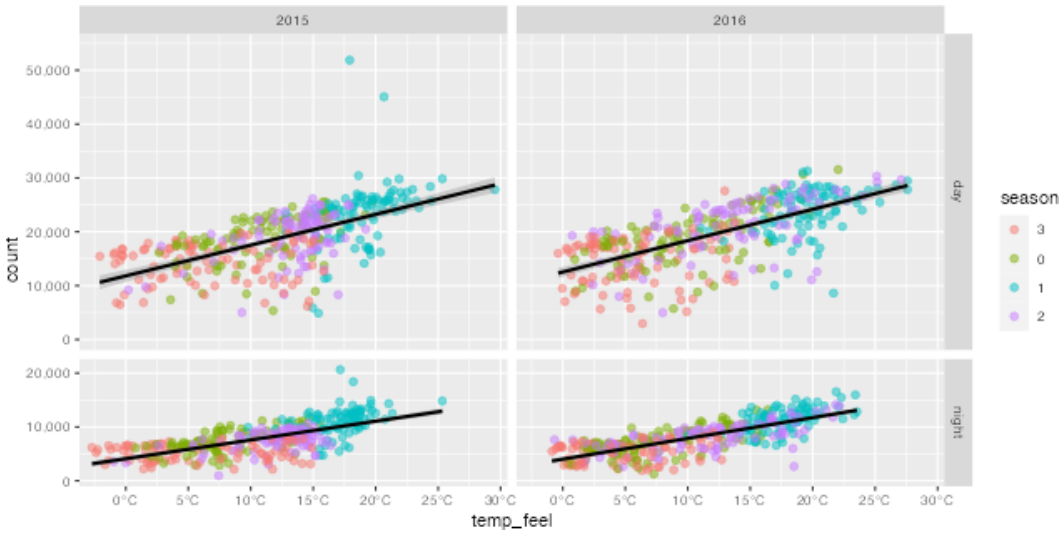


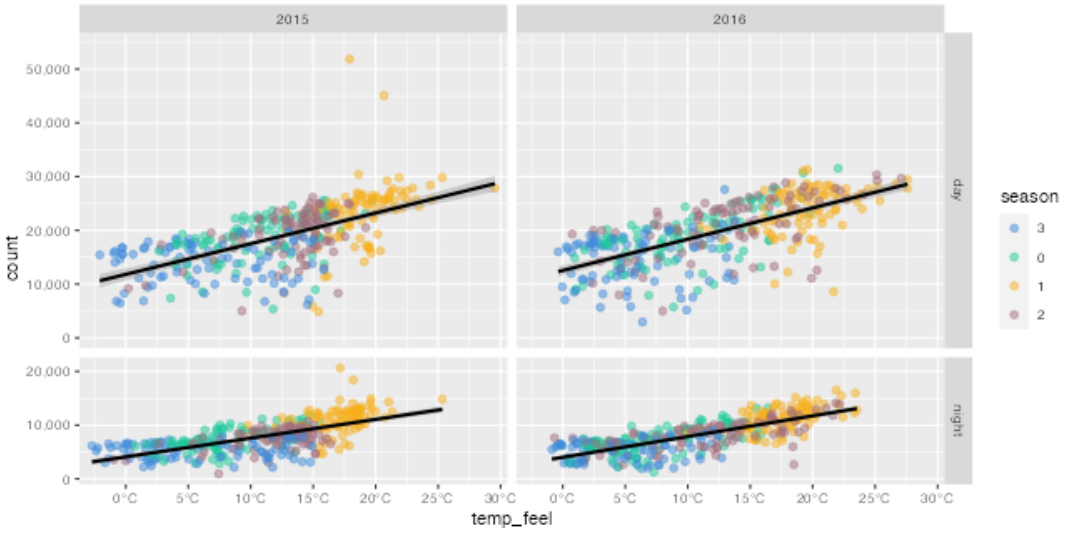
FIGURE 4.7: To adjust the formatting of axis labels, the respective axis needs to be addressed via the `scale_*()` functions.

4.8 Use a custom color palette

The `scales` do not only control the behavior of the axes but also all other aesthetics such as `color`, `shape` or `alpha`. In case of categorical colors, scale_color_manual() enables us to overwrite the default color set by passing a vector of colors.

```
g1 <- ggplot(bikes, aes(x = temp_feel, y = count)) +
  geom_point(
    aes(color = season), alpha = .5, size = 2
  ) +
  stat_smooth(
    aes(group = day_night), method = "lm", color = "black"
  ) +
  facet_grid(
    day_night ~ year, scales = "free_y", space = "free_y"
  ) +
  scale_x_continuous(
    breaks = -1:6*5, labels = function(x) paste0(x, "°C"), expand = c(mult = 0, add = 1)
  ) +
  scale_y_continuous(
    breaks = 0:5*10000, labels = scales::label_comma(), expand = c(mult = .1, add = 0)
  ) +
  ## use a custom color palette for season colors
  scale_color_manual(
    values = c("#3c89d9", "#1ec99b", "#F7B01B", "#a26e7c")
  )
```

```
g1
```



The colors will be applied in order, i.e. the levels of the factor or alphabetical in case of character variables. To ensure correct mapping, one can also use a named vector.

You will learn more about the different color and fill scales and how to manipulate colors in Chapter XYZ. The chapter also features an example how to create a corporate color or fill scale to ensure consistent color use.

Furthermore, we are storing the current plot in an object named `g1`. This `ggplot` object can be extended afterwards. Storing intermediate ggplot outputs is especially helpful if the code becomes rather long and in case you have multiple variants of the same chart, for example when building up a chart stepwise. Another common use case is the creation of graphics in multiple languages.

4.9 Adjust labels

For now, we have ignored that **{ggplot2}** uses the variable names as specified in our `bikes` object for data-related labels. Resist the temptation to change the variable names in your original data set! We can easily overwrite those by referring to the respective aesthetic (`x`, `y`, and `color`) in the `labs()` function which we add to our plot. Here, we can also specify a title, subtitle, caption, and tag (subtitle and tag are not shown in the following example; Fig. 4.8).

```
g2 <- g1 +
  labs(
    ## overwrite axis and legend titles
    x = "Average Feels-Like Temperature", y = NULL, color = NULL,
    ## add plot title and caption
```

```
    title = "Trends of reported bike rents versus feels-like temperature in London.",
    caption = "Data: TfL (Transport for London), Jan 2015-Dec 2016"
  )

g2
```

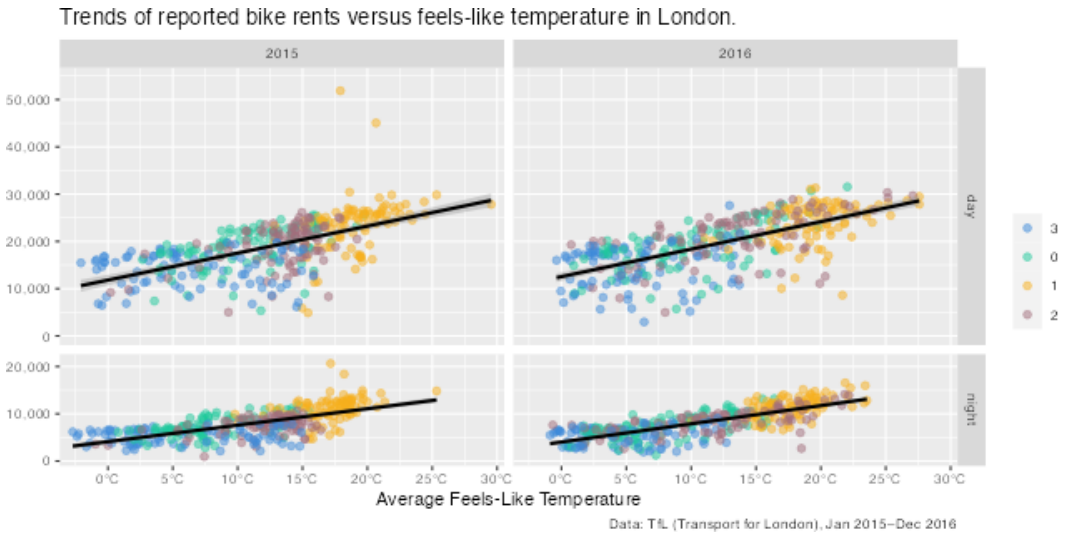


FIGURE 4.8: We can overwrite the default labels with the `labs()` which also allows to add a title, subtitle, caption, and tag to the graphic.

Let's also overwrite the cryptic numeric encoding of the seasons. Similar to the positional scales, we can pass a vector or function to the `labels` argument in the `scale_color_*()` component:

```
g3 <- g2 +
  scale_color_manual(
    values = c("#3c89d9", "#1ec99b", "#F7B01B", "#a26e7c"),
    labels = c("Winter", "Spring", "Summer", "Autumn")
  )

g3
```

Note that the code is returning a message informing you that the present color scale has been replaced. As you can only apply one scale per aesthetic, we also have to pass the color vector again to use the custom colors from before.

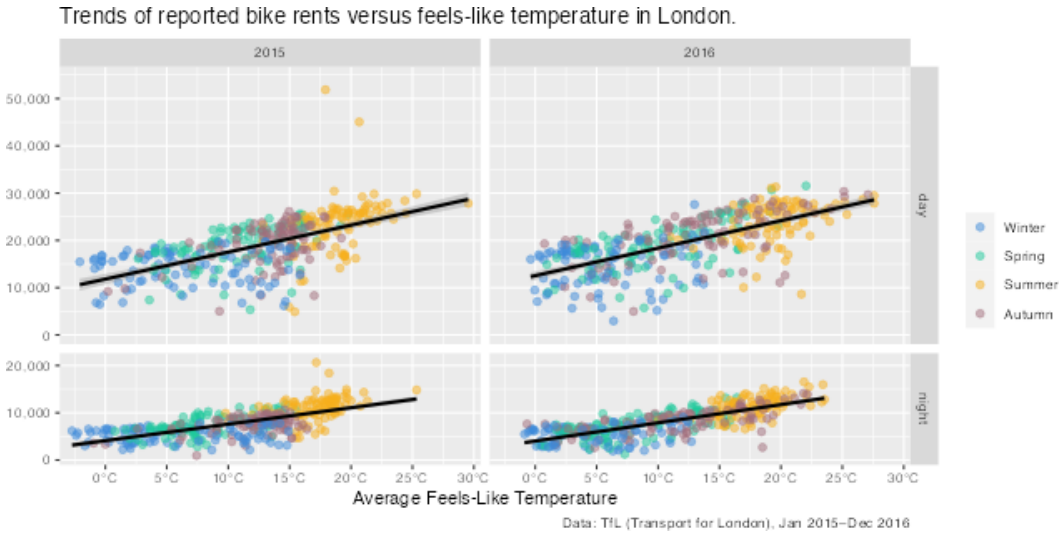


FIGURE 4.9: By passing a vector of the same length as there are seasons to the `labels` argument of the `scale_color_*()` function, we can overwrite the labels used in the legend.

4.10 Apply a complete theme

{ggplot2} comes with a set of so-called *complete themes*. We can add one of these to overwrite the default theme_grey() by one of the others (run `?theme_grey` for a full list of available complete themes).

When adding a theme to a ggplot, we can already overwrite the `base_size` of the theme elements, which translates to the size of text labels and line widths. Furthermore, we can set a non-default typeface by supplying a locally installed typeface in the `base_family` argument.

```
g3 +
  ## add theme with a custom font + larger element sizes
  theme_light(
    base_size = 12, base_family = "Cabinet Grotesk"
  )
```

4.11 Customize the theme

The complete themes follow a set of rules that overwrite the choices made for the default `theme_grey()`. By using a `theme()` call after (!) adding a complete theme, one can adjust the appearance of single elements (e.g. `plot.title` or `panel.grid.major.x`) as well as set some pre-set options such as the positions of titles, captions and legends (`plot.title.position`, `plot.caption.position` and `legend.position`).

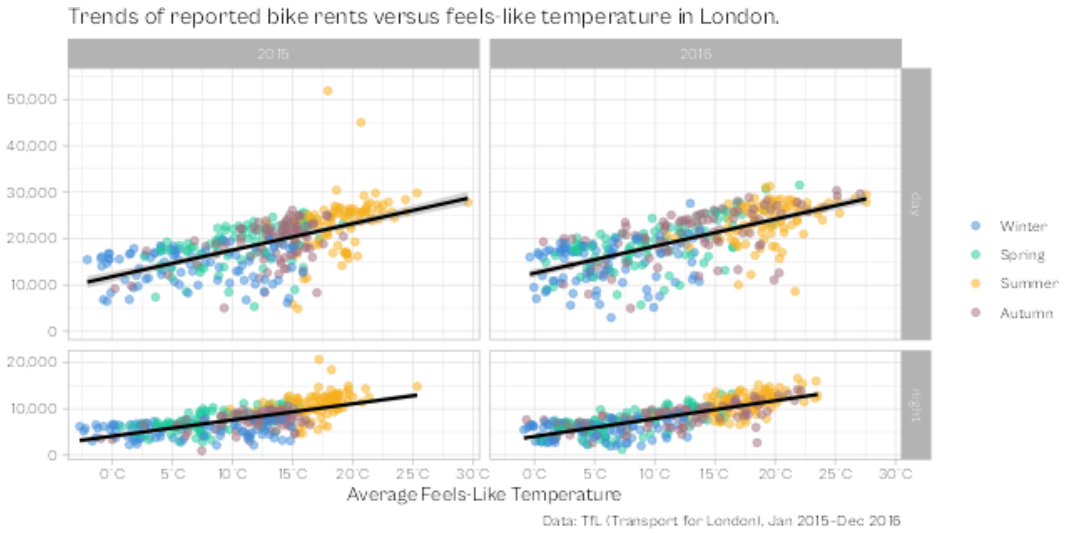


FIGURE 4.10: The graphic now comes with a new look and a non-default font used for all text labels.

In general, theme elements can be of class text (e.g. `plot.title`), line (e.g. `panel.grid.major.x`), or rectangle (e.g. `panel.background`). In addition, we can use `element_blank()` to remove an element entirely as set for `panel.grid.minor` in our example.

```
g3 +
  theme_light(
    base_size = 12, base_family = "Cabinet Grotesk"
  ) +
  ## theme adjustments
  theme(
    plot.title.position = "plot", ## left-align title
    plot.caption.position = "plot", ## right-align title
    plot.title = element_text(face = "bold", size = rel(1.3)), ## larger bold title
    axis.text = element_text(family = "Tabular"), ## monospaced font for axes
    axis.title.x = element_text( ## left-aligned, grey x axis label
      hjust = 0, color = "grey30", margin = margin(t = 12)
    ),
    strip.text = element_text( ## larger bold facet labels
      face = "bold", size = rel(1.15)
    ),
    panel.grid.major.x = element_blank(), ## no vertical grid lines
    panel.grid.minor = element_blank(), ## no minor grid lines
    legend.position = "top", ## place legend above plot
    legend.text = element_text(size = rel(1)) ## larger legend labels
  )
```

The book covers themes in full detail in Chapter XYZ. Here you learn how to leverage complete themes, which other complete themes are provided by extension packages, and

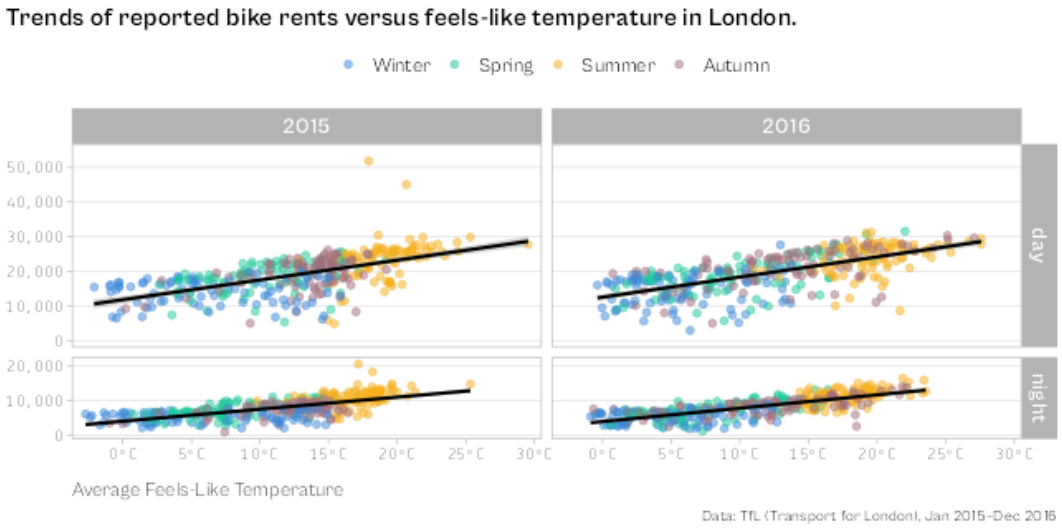


FIGURE 4.11: After applying on of the complete themes, one can further style the theme to the personal needs.

how to create your own custom, corporate theme to apply a cohesive and easily reproducible style to all of your graphics.

[WIP]

RECAP

LEAD OVER TO NEXT CHAPTER

Part I

How To Work with Components

5

Working with Layers

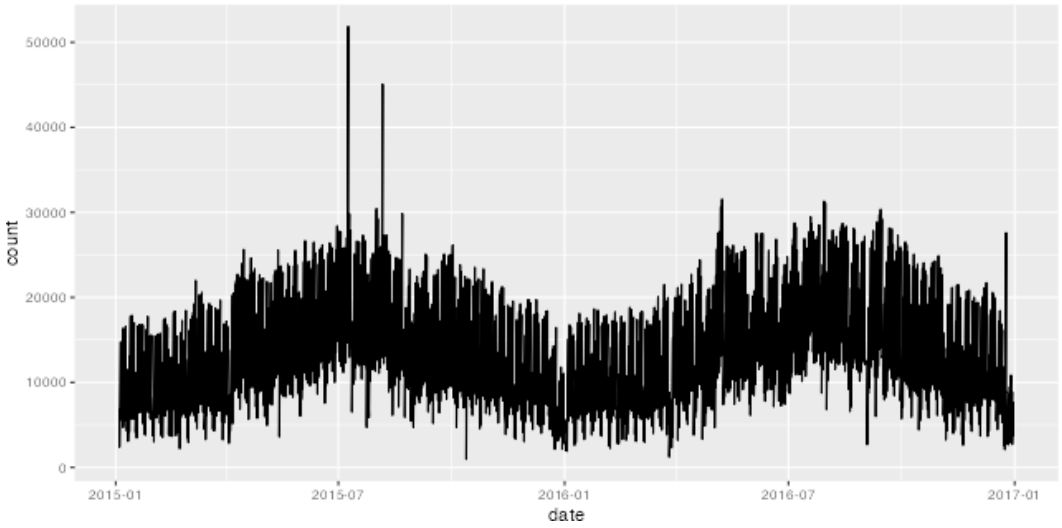
Internally all layers are created by the `layer()` function. A layer is by definition a "combination of data, stat and geom with a potential position adjustment" (`layer` R help).

The long list of featured `geom_*()` and `stat_*()` functions in **{ggplot2}** is thus just a set of predefined layers with default `geom`, `stat`, `position` arguments that use the data passed in the initial `ggplot()` call. The data can also be specified for each layer separately by passing it inside the respective geom or stat.

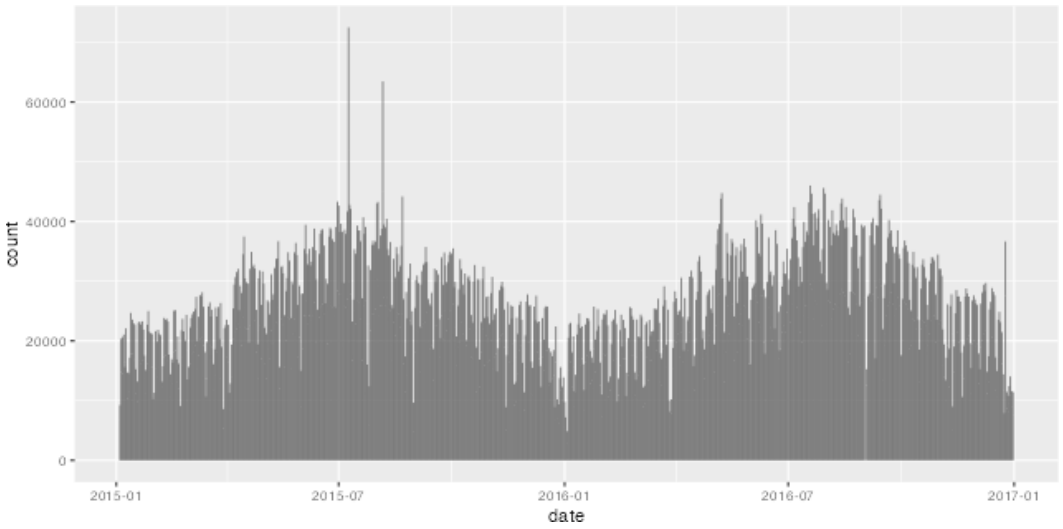
5.1 Geometrical Shapes

Many geometrical shapes only need two positional arguments, namely `x` and `y` as a single coordinate is sufficient to represent your data. A combination of x and y values determine the position of points, connected lines, or the height of bars.

```
ggplot(bikes, aes(x = date, y = count)) +
  geom_line() ## a timeseries of bike shares per date
```




```
ggplot(bikes, aes(x = date, y = count)) +
  geom_col() ## a bar chart with one bar per date
```



[WIP]

- most geoms use two positional aesthetics
- showcase a few of those
- some geoms take only one or more than 2
- showcase of some of those

5.2 Statistical Transformations

- stats are just tak a different perspective
- illustrate with usual examples
- powerful transformations: count + summary

5.3 Positional Adjustments

-

6

Customizing Color Palettes

7

Styling Titles and Labels

Part II

How To Polish Your Graphics

8

Quick Steps to Improve Your Graphic

A

More to Say

Yeah! I have finished my book, but I have more to say about some topics. Let me explain them in this appendix.

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Bibliography

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