Introduction to Multivariate Data Visualization

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Start

> This tutorial is an introduction to data visualization that focuses on the explorative analysis of multivariate (tabular) data and uses interactive examples in R. The tutorial is target at learners of all disciplines—no programming experience required.

Motivation

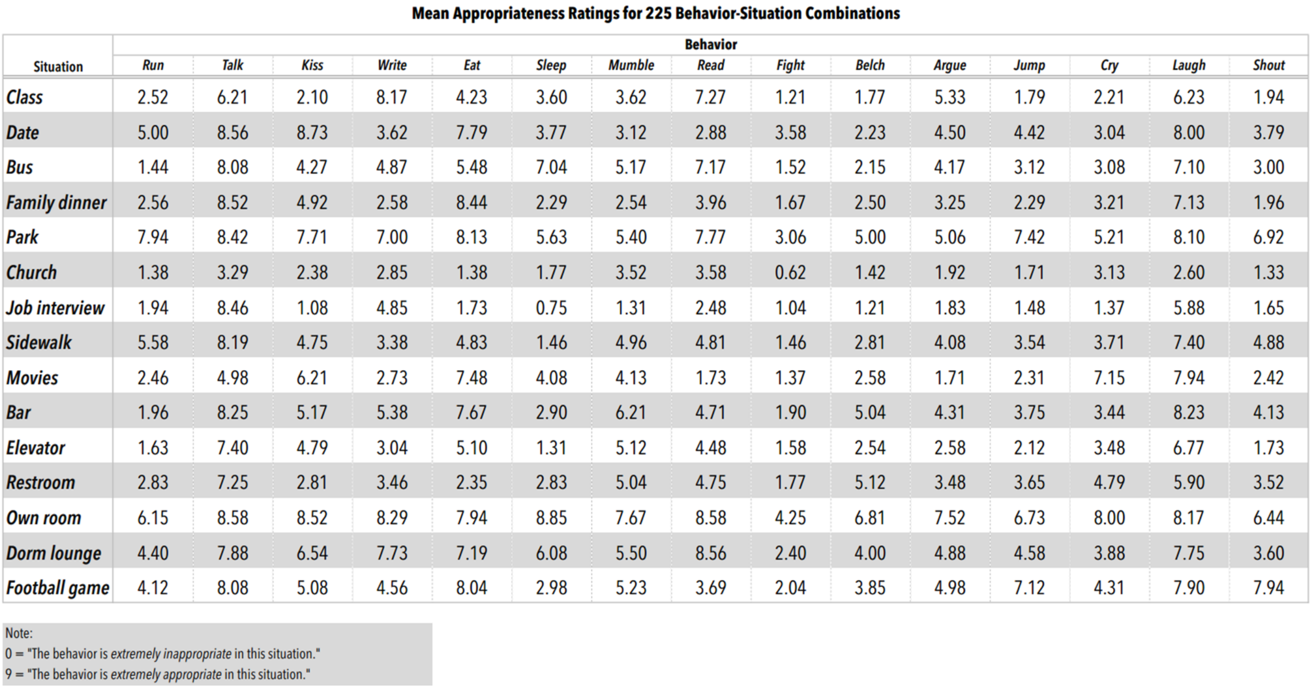
The **goal of data visualization** is to make data readable. Whereas statistics focuses on summarizing data and testing hypothesis, visualization is more explorative. With a visualization, we can get an overview of the data, identify frequent patterns and rare outliers, inspect quality issues, and relate individual data points to the overall data. This is not meant to replace a statistic analysis, but to complement it.

In this tutorial, we focus on **multivariate data**—data that can be represented as tables—because it is one of the most common data types and its visualization is relevant across nearly all scientific areas and domains. The rows of the table usually list the data items, while the columns provide different data variables recorded for each item.

Tables in their plain version are a great tool to show small amounts of data, as well as to edit and transform the data. However, they hardly provide a good overview or reveal patterns and outliers.

Example

For instance, the table below shows study results where participants answered **how appropriate a behavior is in a certain situation** (from 0 – *low* to 9 – *high appropriateness*). It is easy to read a specific value from the table relating to a pair of behavior and situation. An example is that *sleeping* in *church* is not considered appropriate (value: 1.77). But what is the most appropriate behavior in *church*? What is generally a favorable behavior in most situations? Are there other situations rated similarly to *church*? These questions are harder to answer with the plain table, already in rather small example like this.



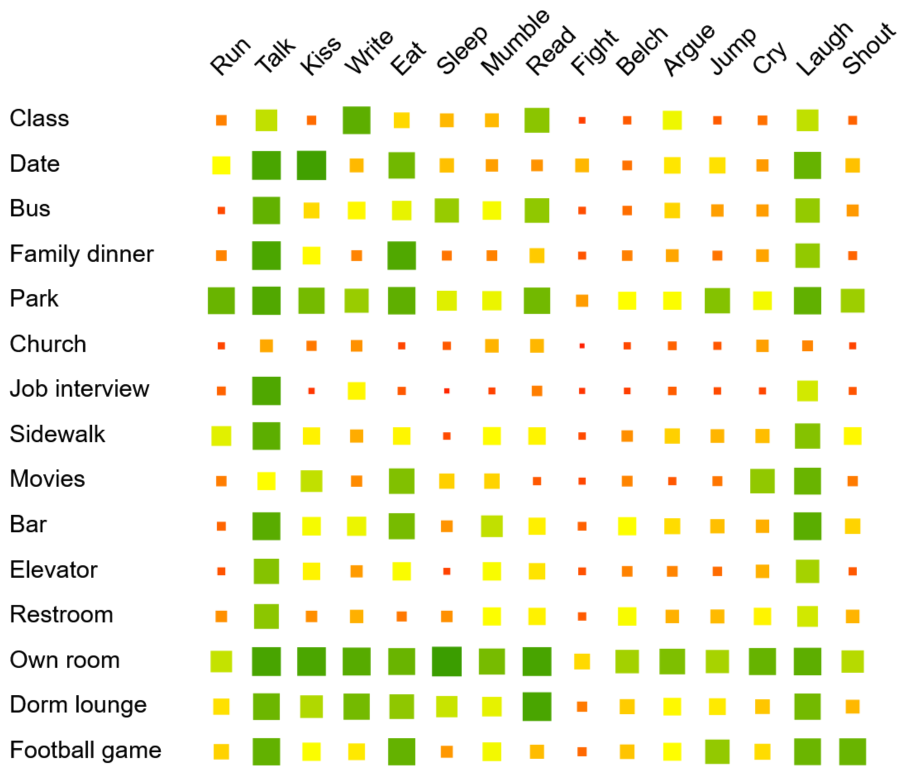
Mean Appropriateness Ratings for 225 Behavior-Situation Combinations

Situation	Behavior														
	Run	*Talk*	*Kiss*	*Write*	*Eat*	*Sleep*	*Mumble*	*Read*	*Fight*	*Belch*	*Argue*	*Jump*	*Cry*	*Laugh*	*Shout*
Class	2.52	6.21	2.10	8.17	4.23	3.60	3.62	7.27	1.21	1.77	5.33	1.79	2.21	6.23	1.94
Date	5.00	8.56	8.73	3.62	7.79	3.77	3.12	2.88	3.58	2.23	4.50	4.42	3.04	8.00	3.79
Bus	1.44	8.08	4.27	4.87	5.48	7.04	5.17	7.17	1.52	2.15	4.17	3.12	3.08	7.10	3.00
Family dinner	2.56	8.52	4.92	2.58	8.44	2.29	2.54	3.96	1.67	2.50	3.25	2.29	3.21	7.13	1.96
Park	7.94	8.42	7.71	7.00	8.13	5.63	5.40	7.77	3.06	5.00	5.06	7.42	5.21	8.10	6.92
Church	1.38	3.29	2.38	2.85	1.38	1.77	3.52	3.58	0.62	1.42	1.92	1.71	3.13	2.60	1.33
Job interview	1.94	8.46	1.08	4.85	1.73	0.75	1.31	2.48	1.04	1.21	1.83	1.48	1.37	5.88	1.65
Sidewalk	5.58	8.19	4.75	3.38	4.83	1.46	4.96	4.81	1.46	2.81	4.08	3.54	3.71	7.40	4.88
Movies	2.46	4.98	6.21	2.73	7.48	4.08	4.13	1.73	1.37	2.58	1.71	2.31	7.15	7.94	2.42
Bar	1.96	8.25	5.17	5.38	7.67	2.90	6.21	4.71	1.90	5.04	4.31	3.75	3.44	8.23	4.13
Elevator	1.63	7.40	4.79	3.04	5.10	1.31	5.12	4.48	1.58	2.54	2.58	2.12	3.48	6.77	1.73
Restroom	2.83	7.25	2.81	3.46	2.35	2.83	5.04	4.75	1.77	5.12	3.48	3.65	4.79	5.90	3.52
Own room	6.15	8.58	8.52	8.29	7.94	8.85	7.67	8.58	4.25	6.81	7.52	6.73	8.00	8.17	6.44
Dorm lounge	4.40	7.88	6.54	7.73	7.19	6.08	5.50	8.56	2.40	4.00	4.88	4.58	3.88	7.75	3.60
Football game	4.12	8.08	5.08	4.56	8.04	2.98	5.23	3.69	2.04	3.85	4.98	7.12	4.31	7.90	7.94

Note:
0 = "The behavior is *extremely inappropriate* in this situation."
9 = "The behavior is *extremely appropriate* in this situation."

- *Source:* "Behavioral Appropriateness and Situational Constraint as Dimensions of Social Behavior" Price, R.H. and Bouffard, D.L. Journal of Personality and Social Psychology, 1974, Vol. 30, No.4, 579-586; via: http://research.jagoda.ca/j/data-sketches/index.html (http://research.jagoda.ca/j/data-sketches/index.html)

By using colored squares as cells, we can **transform the table into a visualization**. We use orange for low values and green for high values. Additionally, we vary the sizes of the squares according to the appropriateness to make it even easier to read, also considering that some users might be red-green blind. This is a straightforward way to visualize multivariate data, but a quite powerful approach already. For instance, we can now see that *job interview* has very similar values as *church*, and opposite to that are *park* and *own room*.



This is just one example to motivate that the use of visualization can be a powerful tool for data analysis.

There are also other visualization methods for such tabular data, some that scale to much larger datasets. We will explain some important ones in this tutorial step by step.

Structure of this Tutorial

As the **main content of this tutorial**, we will introduce you to multivariate data and how to visualize such information. After clarifying the type of data (Multivariate Data), we will first look at visualizations that visualize the data from each variable separately (Univariate Analysis). Then, we also discuss visualization that show multiple variables at the same time (Multivariate Analysis). Along introducing the visualization techniques, we will also discuss their advantages and limitations, as well as their potential to be misinterpreted or misused.

Using R, we will give practical examples how to create these visualization with a few lines of code. We include short interactive quizzes to immediately allow you to check whether you understood the discussed content and can use the visualization to get insights.

Multivariate Data

Before presenting and discussing different visualization options, we first explain what exactly we consider as *multivariate data*. We also introduce a specific dataset that we use as our running example throughout this tutorial.

Multivariate data, as focused in this tutorial, concerns any data that can be represented as:

- **Data items** that represent real-world objects, persons, organization, etc., and
- **Variables** that characterize these items and can be considered as properties or attributes of the items.

Since all items of one dataset are described along the same variables, it is important that the items belong to the same class of objects. Otherwise, it would be hard to apply the same variables. For instance, mixing persons with countries in one dataset, it would be hard to find any attributes that apply to both classes of items alike.

Aside identifiers and names, we can discern between two main data types for those variables:

- **Numeric** variables, which encode some type of number (e.g., positive integers for quantities, float numbers 0.0 to 1.0 for fractions).
- **Categorical** variables, which assign a data item to a certain category (e.g., a country item to a region category).

Hence, these two types encode quantitative and qualitative information. While numeric variables can be sorted in increasing or decreasing order, categorical variables often cannot. Please note that, sometimes, categorical variables are encoded as numbers (e.g., a numeric country code)—analyzing them as numeric variables would result in invalid results.

Our Sample Dataset

We have selected a dataset that is easy to understand, yet of high relevance to many disciplines. It lists the **countries of the world** as data items and characterizes them along **social and economic properties in 2010** as variables. The data is based on free material from GAPMINDER.ORG (https://www.gapminder.org), CC-BY LICENSE.

Let us load our dataset with R and display it as a table. We import it from a **csv** file, a simple file format for tables that consists of of **c**omma-**s**eparated **v**alues (https://en.wikipedia.org/wiki/Comma-separated_values), including also the table header in the first line of the file. In order to see the top 5 rows, we use the function head().

```
world <- read.csv("https://raw.githubusercontent.com/vis-uni-bamberg/mv-vis/main/data/worl
d_dataset.csv", header=TRUE)
head(world)
```

```
##               country   region population income health_expenditure
## 1         Afghanistan     Asia   29200000   1960               37.7
## 2             Albania   Europe    2950000  10800              241.0
## 3             Algeria   Africa   36000000  11000              178.0
## 4             Andorra   Europe      84500  43600             3100.0
## 5              Angola   Africa   23400000   7690              123.0
## 6 Antigua and Barbuda Americas      88000  18200              690.0
##   life_expectancy babies_per_woman
## 1            59.9             5.82
## 2            77.6             1.65
## 3            76.3             2.89
## 4            82.3               NA
## 5            59.9             6.16
## 6            76.6             2.13
```

The dataset contains mostly numeric variables, but also a column with an identifier (the country name) and one with a categorical variable (the region). In detail, we have included the following variables:

- `country` (identifier) – the name of the country
- `region` (categorical) – the geographic region the country is located
- `population` (numeric) – the number of inhabitants of a country
- `income` (numeric) – the gross domestic product (i.e., the average economic production) per citizen in international dollars
- `health_expenditure` (numeric) – the average health spending per citizen in USD
- `life_expectancy` (numeric) – the expected number of years a newborn child would live under current conditions
- `babies_per_woman` (numeric) – the fertility rate, which is number of babies that would be born per woman under current conditions

You can also observe some missing values (`NA` – *not available*). It is a common problem in all real world data that, due to different reasons, there are gaps and quality issues in the data. We intentionally kept the countries with such missing data to literally draw a more realistic picture of the data. Please note, however, that the R scripts in the following often produce warnings relating to these missing values. But these are good reminders that, when interpreting the visualizations, we need to be careful as not all data items might be present.

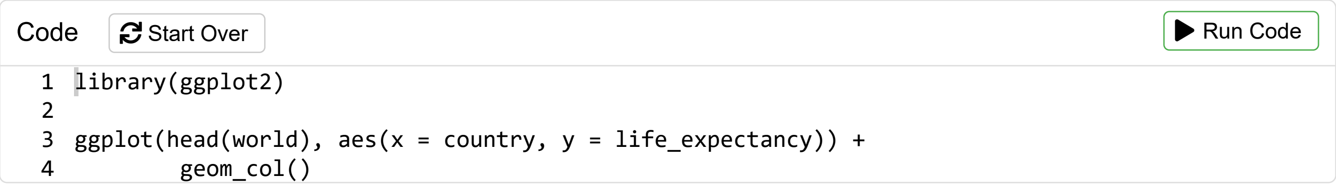
Univariate Analysis

Every variable describes a relevant attribute of the data items. Hence, analyzing the data along only one variable at first (*univariate analysis*), might already provide relevant insights. For instance, we could learn how the items are distributed across a numeric scale (e.g., with a peak around a certain value or evenly across all possible values) or discover noteworthy outliers and extreme values. We will present some simple, yet powerful visualizations to explore such characteristics.

Item Bars

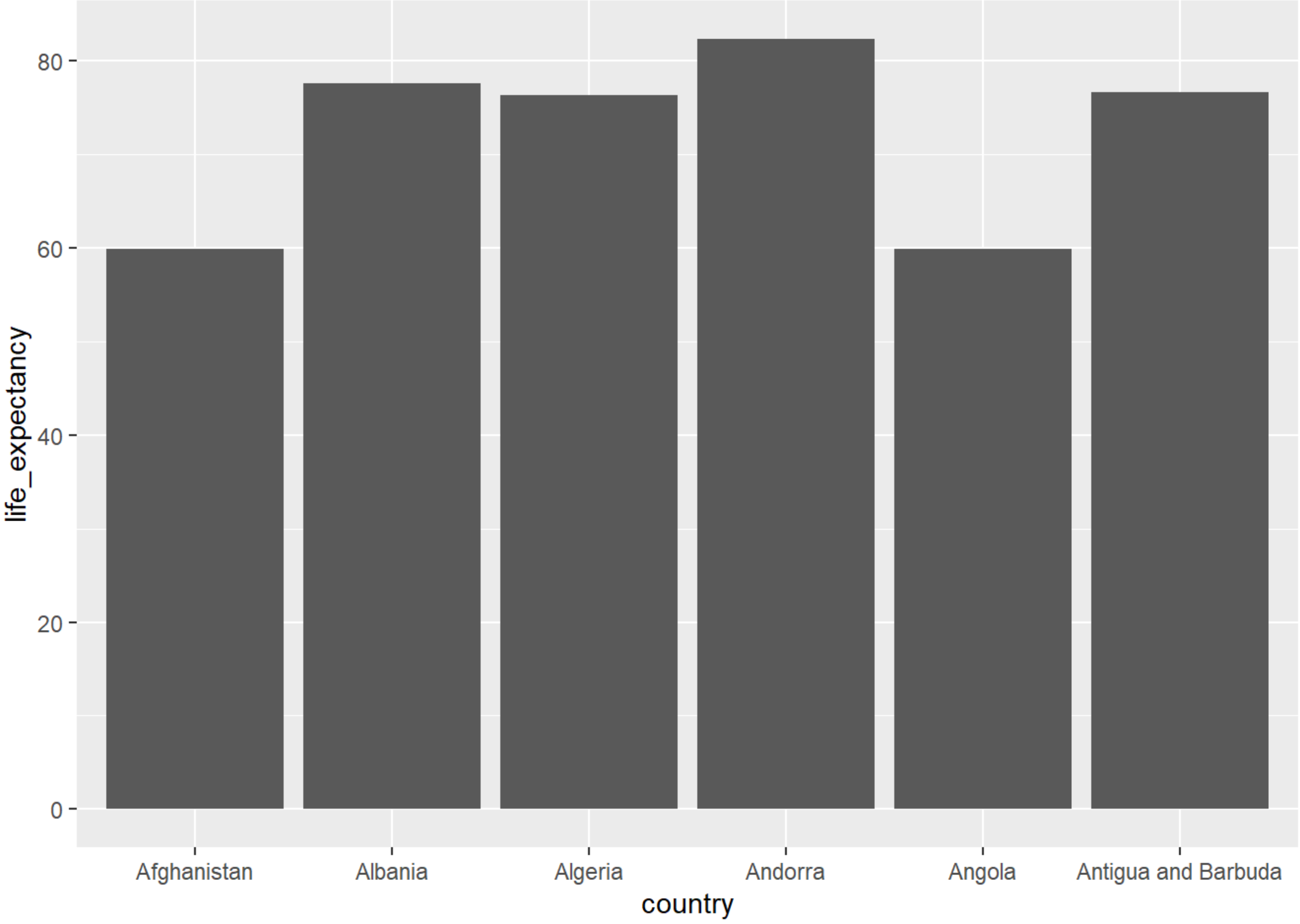
A set of numeric values can be generally represented as **bar charts**. This type of diagram is also applicable here and provides maybe the simplest visualization of a single variable. In such a diagram, each data item is represented by a bar and the height of the bar encodes the respective numeric value.

We can test this, for instance, for the variable `life_expectancy` using the following code. (Please click *Run Code* to see the diagram.)



```
library(ggplot2)

ggplot(head(world), aes(x = country, y = life_expectancy)) +
        geom_col()
```



The code starts with importing the program library ggplot2 (https://ggplot2.tidyverse.org/), a popular visualization library for R. Then, we can generate a bar chart using the function `ggplot()` with `geom_bar()` . First, we provide the data (here, `head(world)` —only the first five rows to not overload the diagram) and specify the **aes***thetic mapping* (here, the mapping of the data to x- and y-axis). Second, we define a **geom***etric layer* as bars or **col***umns*, respectively (`geom_col`).

Please note that we assume here the data is still loaded—in this and the following code blocks, for brevity, we do not repeat code that has been executed before like loading of data or libraries.

TASK: You can change the above code and run it again. Please load **all** countries and analyze the data ranges.

What range of values do you observe for `life_expectancy` ?

○ The values are between 20 and 90.

○ The values are between 30 and 85.

○ The values are between 40 and 85

○ The values are between 40 and 90.

Submit Answer

Histograms

With the above diagram, we can hence read specific values and inspect the data range of a certain variable. While this is a good starting point, we might also want to understand whether the data distribution has a certain peak around a value, which is hard to see in the example above. To this end, histograms show how frequent certain values are. A typical example for a historgram, which most likely everybody has seen in school or at university, is a distribution of grades published after an exam.

When there are discrete steps in the data—for instance, the steps of a grading scale—, each bar can represent one of these steps. However, for continuous numeric variables, it does not make sense to include a bar for every different value because, most likely, none of the values is repeated. Instead we use **bins** of values that cover a certain range, each of the same width. For generating a histogram, we can either specify the number of bins we want to have or the width of the bins. Here, we use the number of bins as this can be set independently of the scale of the variable.

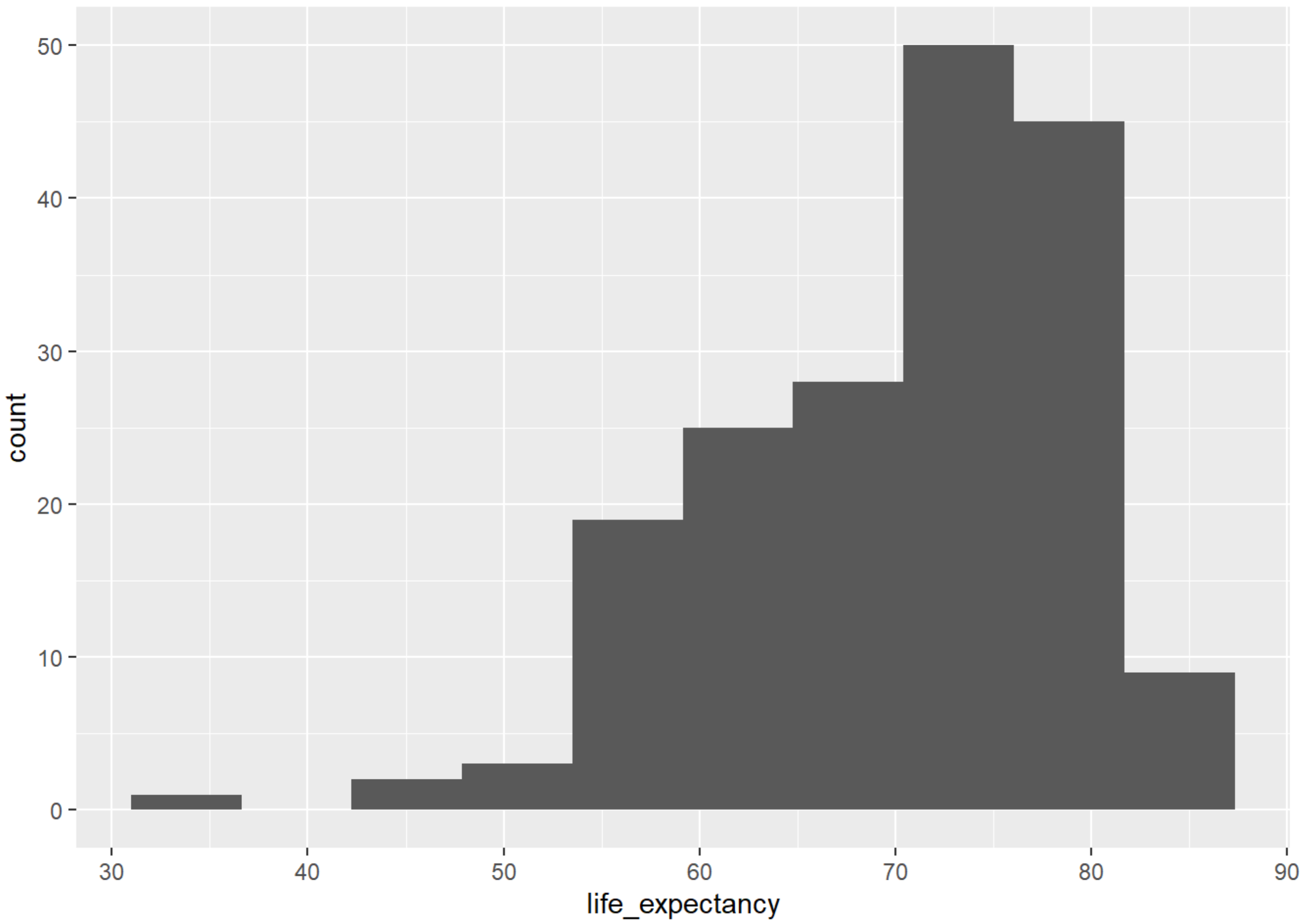
For our sample dataset, we can generate a histogram for the variable `life_expectancy` as follows.

Code ↻ Start Over ▶ Run Code

```
ggplot(world, aes(x = life_expectancy)) +
        geom_histogram(bins = 10)

```

```
Warning: Removed 5 rows containing non-finite values (stat_bin).
```



Again, we use `ggplot()` , but now with `geom_histogram()` to select the right type of diagram. We set the number of `bins` to 10.

TASK: In the above code, please change the variable to `babies_per_woman` and analyze how the distribution adapts.

What do you observe for the distribution of values regarding `babies_per_woman` ?

○ The peak is on the left for small values.

○ The peak is in the middle for medium values.

○ The peak is on the right for high values.

○ There is no clear peak.

Submit Answer

Boxplots

Boxplots even aggregate the data more, by computing statistical properties of the numerical data distributions and visualizing these. Important to understand is that the visualized properties are based on sorting all values that appear for the variable and then cutting them into four equally-sized parts, the **quarters**. For visualization as a boxplot, we are specifically interested in the values at the borders of the quarters, which are called **quartiles**:

- **First quartile** – the value at the border of the first and second quarter
- **Second quartile (median)** – the value in the middle of the sorted list at the border of the second and

third quarter
- **Third quartile** – the value at the border of the third and fourth quarter

Describing the distribution along the quartiles gives a good summary where there is a peak (mostly, around the median) and where the central 50% of the points are (between the first and third quartile). Boxplots draw a box for these values spanning from the first to the third quartile, with a thick line at the median value.

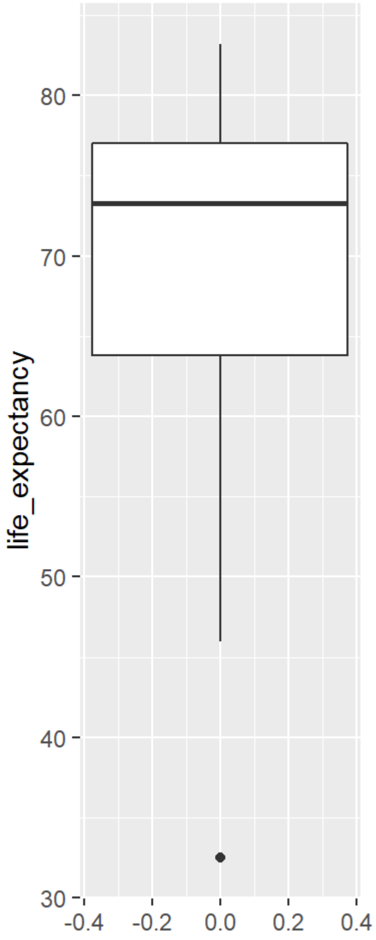
Here is an example for the variable `life_expectancy` .

Code Start Over Run Code

```
ggplot(world, aes(y = life_expectancy)) +
        geom_boxplot()

```

```
Warning: Removed 5 rows containing non-finite values (stat_boxplot).
```



We can easily read the three quartile values from the box. But we also see that there are a few more visual elements contained in the boxplot. Vertical lines, the **whiskers**, extend the box at the bottom/top. Each marks how far the distribution stretches in the first/fourth quarter. We actually need to discern two different cases, which we also see in the example: First, if the values in the first/fourth quartile do not stretch too far, the whisker goes down/up to the minimum/maximum value (here, this applies to the fourth quartile above the box). Second, if there are some values that should be rather considered as outliers, the whisker only stretches to the minimum/maximum of the non-outliers and outliers are visualized as separate dots (here, this applies to the first quartile below the box with a single outlier). Usually, values that are above/below the box with 1.5 times the distance between the first and third quartile (**inter-quartile range**) are considered as outliers.

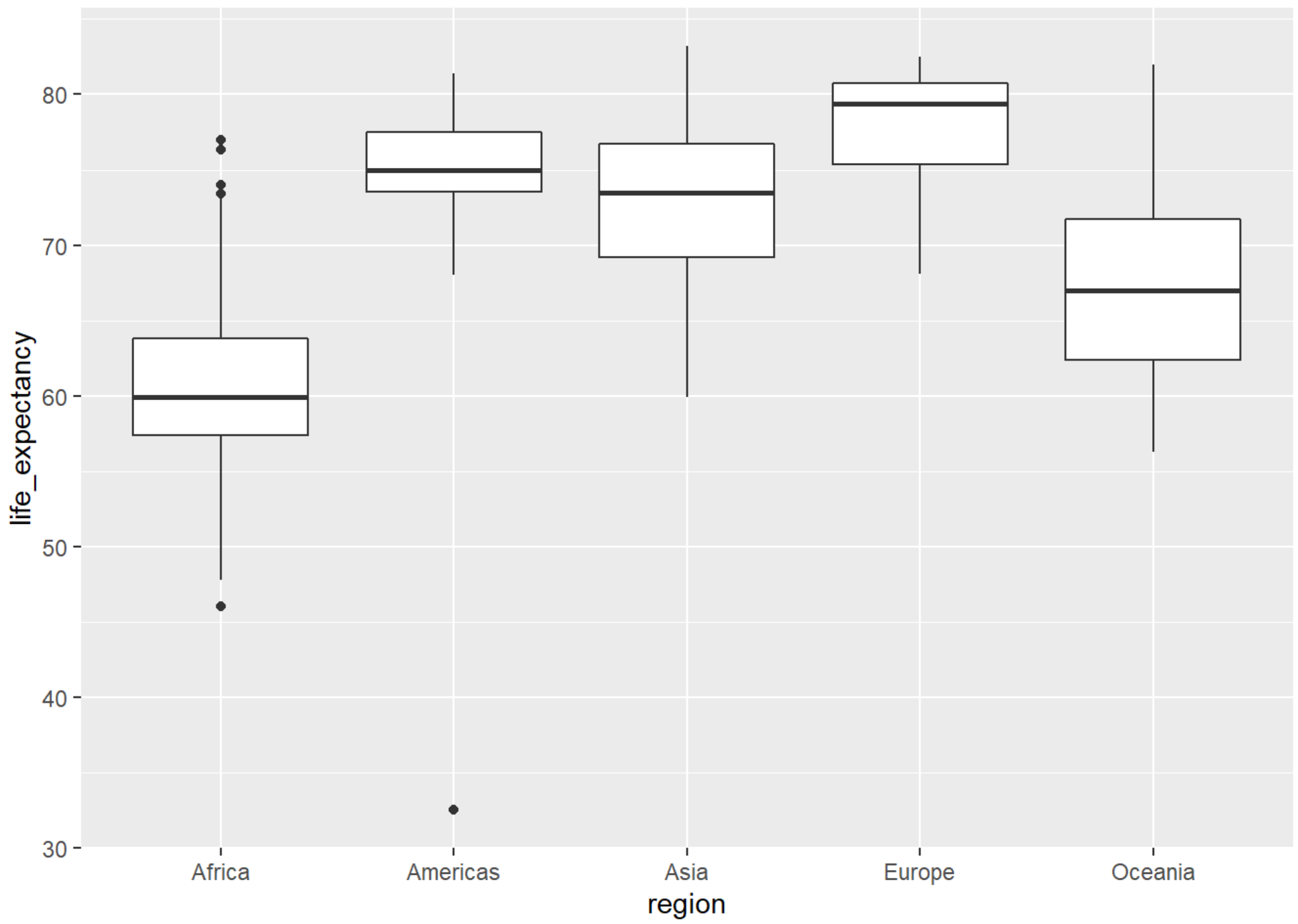
With this you can get a compact overview of the distribution of the data. It now allows us to visualize multiple boxplots next to each other comparing different groups of data items. For instance, we can split the above data distribution by region as follows.

Code Start Over ▶ Run Code

```
ggplot(world, aes(x = region, y = life_expectancy)) +
        geom_boxplot()

```

```
Warning: Removed 5 rows containing non-finite values (stat_boxplot).
```



Now, we note that, generally, African countries suffer from lower life expectancy than all other regions, which have clearly higher values. However, there are numerous outliers regarding African countries to the bottom and top. Surprisingly, though, the overall lowest value, which we already noted as an outlier in the aggregated boxplot above, is located in the Americas.

To identify the specific countries with the lowest life expectancy, let us sort the original data table. Here is an example how this works for listing the top countries by population in decreasing order:

Code Start Over ▶ Run Code

```
head(world[order(-world$population), ])


```

```
                     country   region population income
35                     China     Asia   1.37e+09   8890
76                     India     Asia   1.23e+09   4230
179 United States of America Americas   3.09e+08  54400
77                 Indonesia     Asia   2.42e+08   8290
24                    Brazil Americas   1.96e+08  14900
128                 Pakistan     Asia   1.79e+08   3910
    health_expenditure life_expectancy babies_per_woman
35               221.0            75.8             1.59
76                54.3            66.7             2.60
179             8360.0            78.7               NA
77                76.9            69.7             2.48
24               990.0            74.4             1.81
128               21.8            64.3             3.86
```

TASK: Sort the table by `life_expectancy` with increasing order to answer the following question.

Which is the country with the lowest value for `life_expectancy`?

○ Bolivia

○ Guyana

○ Haiti

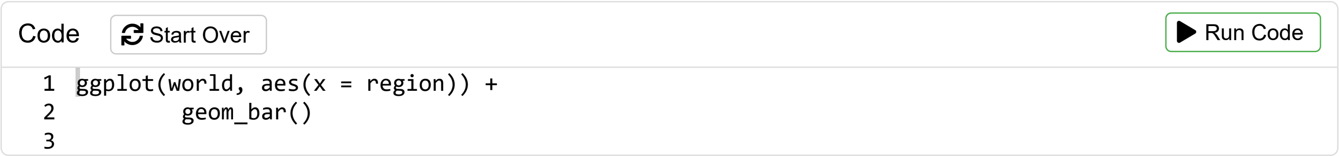
○ Suriname

Submit Answer

Discussion

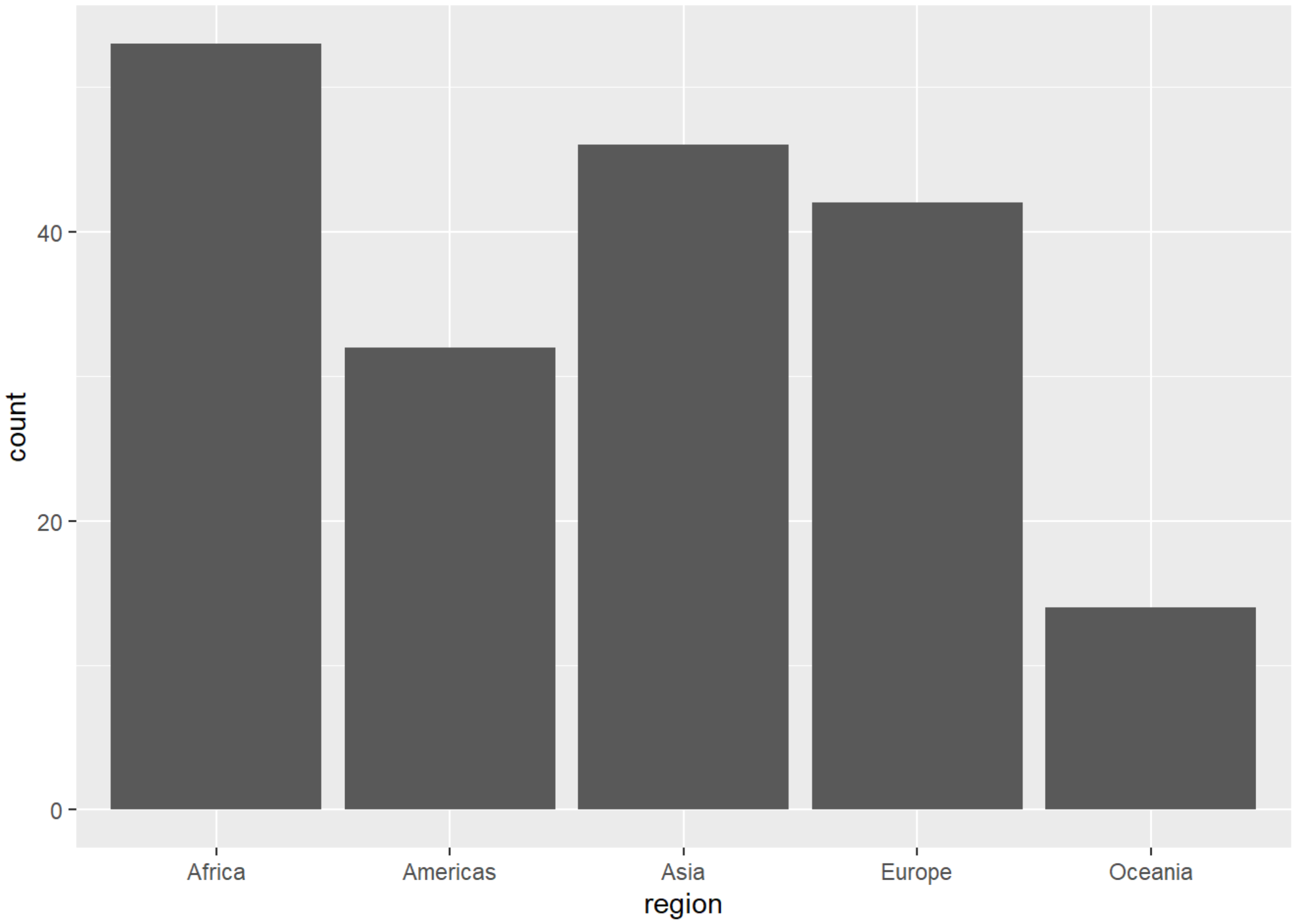
We have seen three ways of visualizing a single numeric variable with **increasing level of aggregation**, from item bars to boxplots. First, the item bars show the data pretty much *as is* and directly map each numeric value to a single bar. When loading many data items, this can quickly become too cluttered as there is not enough space for putting all the labels and bars get very thin. Also, while one can easily see the general range of data, it is hard to really judge the distribution of data points. For this, histograms are much better. They abstract from individual items and show frequency of items regarding a specific range of values. Here, the range of values as well as peaks become obvious. Whereas histograms are already use some aggregation, boxplots go beyond and are even more space-efficient. In a single column, they show various properties of the data distribution of one variable. Multiple boxplots can be placed next to each other to compare subsets of data items regarding one variable.

Our discussion has focused on numerical variables here and **categorical variables** cannot be visualized just like that. For instance, for the item bars, there is no numeric value we can map the height of the bar to. Also, boxplots heavily rely on characterizing quantitative properties such as quartiles, which are not available for categorical variables. Histograms, however, can be applied to categorical data with certain restrictions: We can count for each category how many data items are assigned and visualize these frequency values. However there are no bins as categorical scales do not have ranges. Generally, the sorting of the categories is not clearly defined, but sorting by alphabetic order or item frequency often makes sense. Let us give an example here for the number of countries each `region` contains, sorted by alphabetic order of regions.



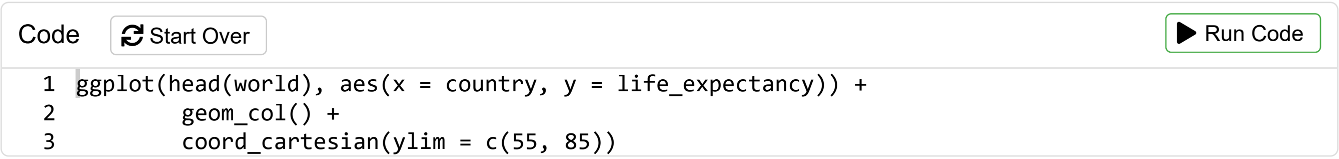
```r
ggplot(world, aes(x = region)) +
        geom_bar()

```

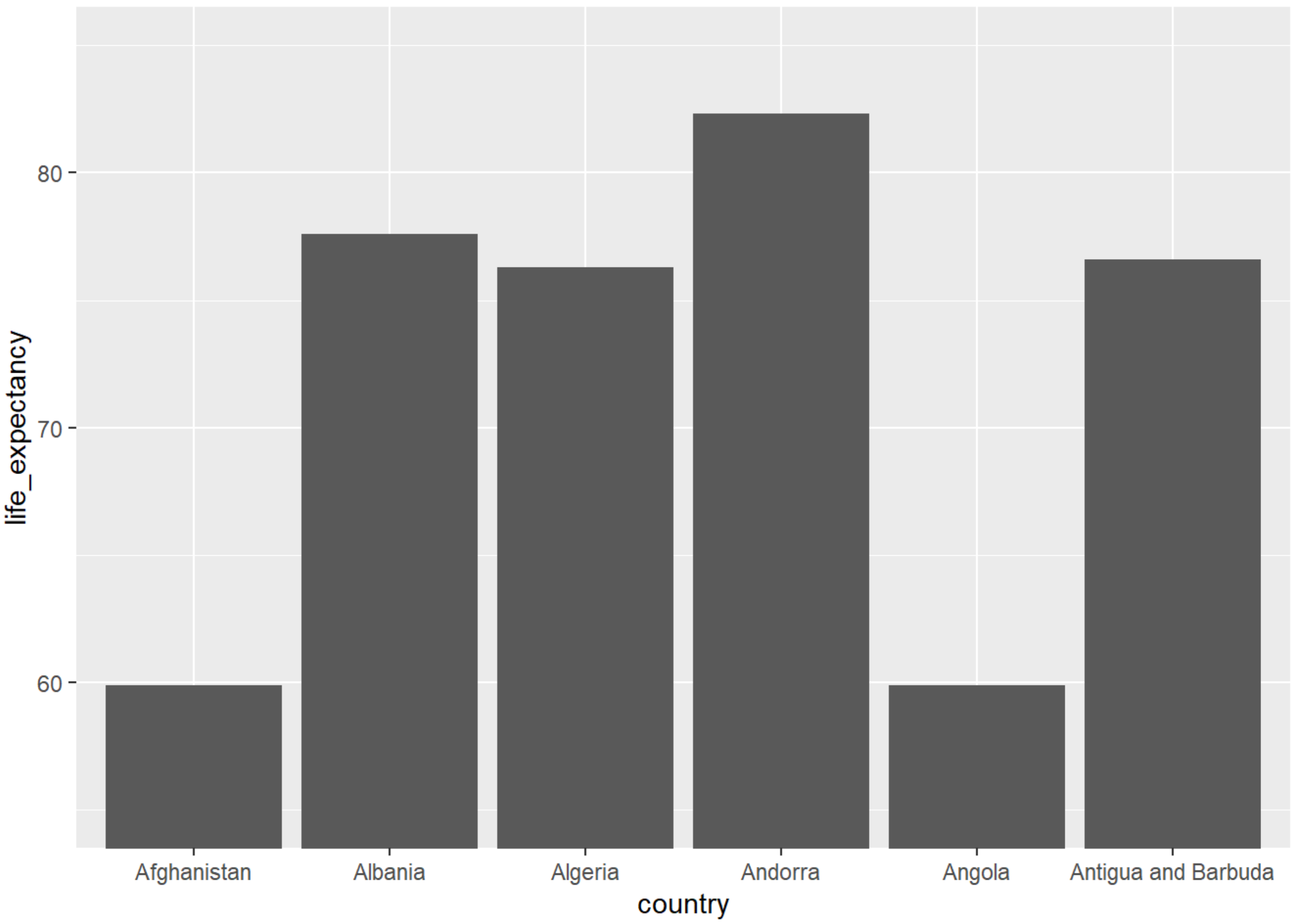


Misinterpretation and Misuse: Though being simple, the above diagrams already might be misinterpreted or even intentionally misused. For instance, you can sometimes see news articles trick their readers by cutting the scale of item bars to visually exaggerate differences and make the story appear more important. Histograms can be misinterpreted when using too many bins—random variations in the data will likely cause certain differences of neighboring bars that should not be interpreted as being relevant. Too few bins can hide relevant patterns in the data. Since boxplots also aggregate the data, something similar can be observed here. For instance, if there are several distinct peaks, the boxplot would hide this within the main rectangle and appears as if there is a single peak around the shown median value. Hence, boxplot should only be applied when being sure that the data distribution has a clear single peak, which can be checked using histograms.

As an example for **exaggeration of differences**, we here cut the scale for `life_expectancy` to values between 55 and 85:



```r
ggplot(head(world), aes(x = country, y = life_expectancy)) +
        geom_col() +
        coord_cartesian(ylim = c(55, 85))
```



Multivariate Analysis

Multivariate analysis deals with many variables simultaneously and aims at discovering potential relationships, patterns, and unexpected observations (outliers). One of the most natural and straightforward visualization for multivariate data is a **tabular visualization**, similar as already described earlier (Motivation). Simply coloring the cells of a table according to the cells' values makes a tabular representation much more efficient to process and allows finding basic patterns. Still, relationships between variables might be harder to see and the ability to show many data items remains limited. In the following, we present different common visualization techniques that are useful in these regards for exploring multivariate data.

Scatterplots

With the initial goal to compare the data along two variables, we can create a scatterplot. It uses **points** to represent individual values for two numerical variables **in a coordinate system with two dimensions**. The position of each point in the coordinate system indicates the values for an individual data item on the horizontal x-axis (first variable) and vertical y-axis (second variable).

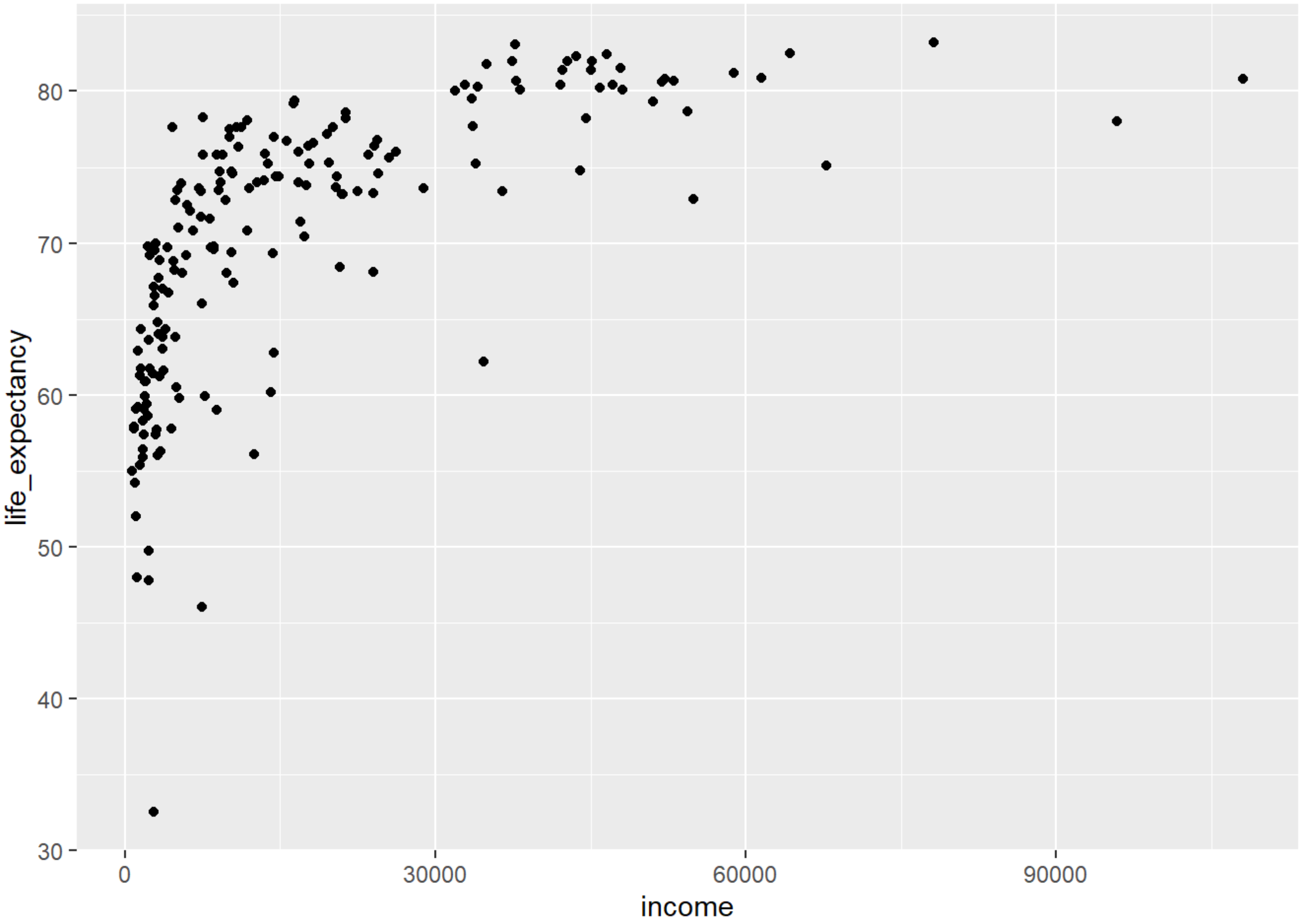
The following code snippet gives an example of a scatterplot showing the data points (countries) along `income` and `life_expectancy`.

Code Start Over ▶ Run Code

```
ggplot(world, aes(y = life_expectancy, x = income))+
        geom_point()

```

```
Warning: Removed 5 rows containing missing values (geom_point).
```



A scatterplot can reveal unexpected gaps in the data or outliers. Again, Haiti (represented by the extreme bottom left point) shows as an outlier for `life_expectancy` . However, it is an outlier that follows a general trend. When we look at the plot as a whole, we observe this trend: As we move from left to right on the horizontal axis for `life_expectancy` , we see a general increase in the `income` values. We say that the variables are *positively correlated* (please note the mathematical concept of correlation (https://en.wikipedia.org/wiki/Correlation)). Negative correlations, hence, would show as decreasing values from left to right, while other combinations might not show any clear trend at all.

TASK: Use the above code block to observe pairwise relationships (e.g., positive, negative, or no correlation) between different pairs of variables and try to answer the following question.

Which of the following statements about pairwise correlations is true?

○ The variables `income` and `life_expectancy` are negatively correlated.

○ There is no clear correlation between `babies_per_woman` and `life_expectancy`.

○ In countries with low income, women are likey to have more babies.

○ The variables `income` and `population` have a positive correlation.

Submit Answer

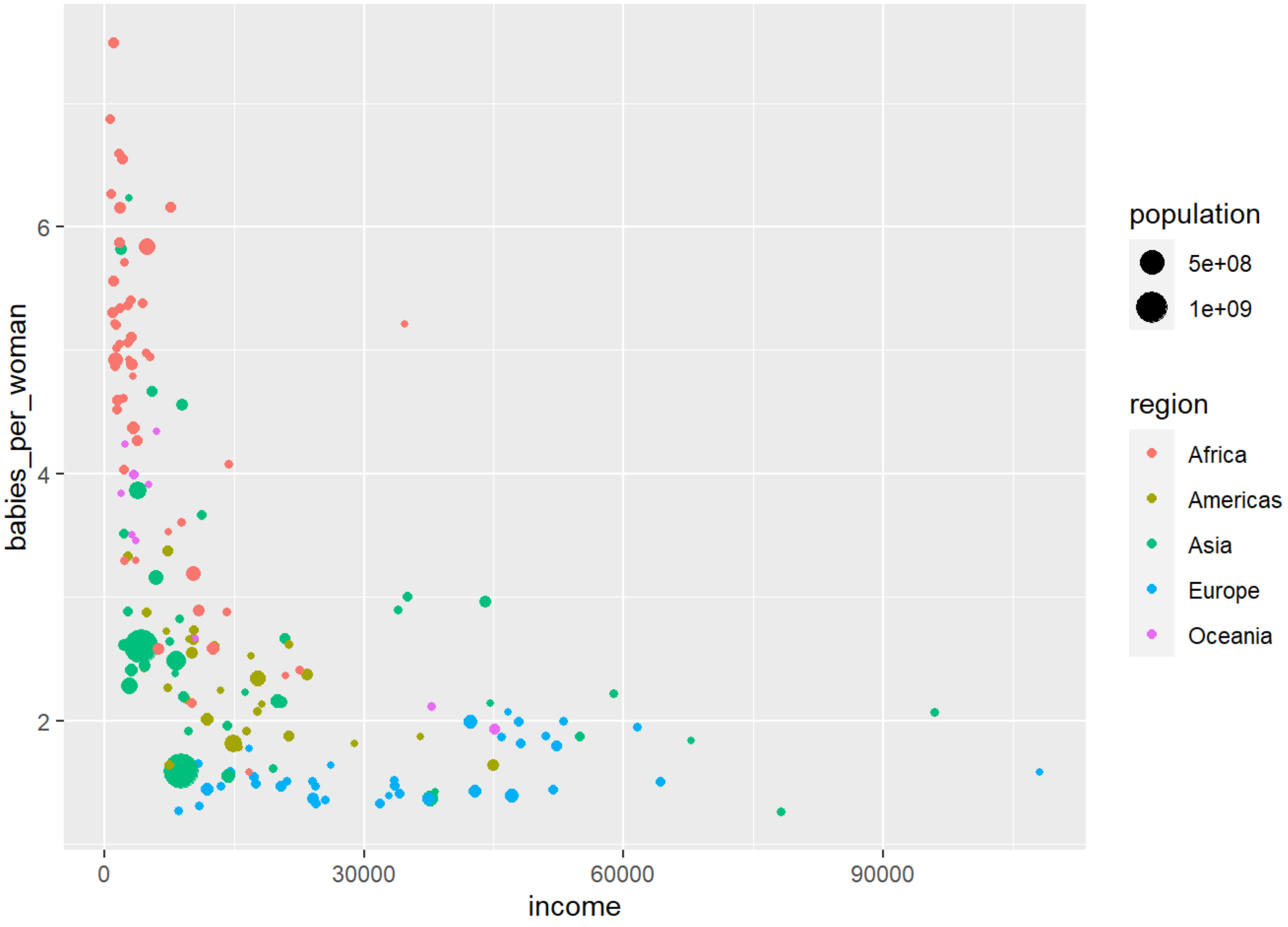
A nice property of scatterplot is that they can be visually extended to also show data from a few more variables. For instance, we can use the color of the points to encode `region` and the size of the points to visualize `population`.

Code Start Over ▶ Run Code

```
ggplot(world, aes(x=income, y=babies_per_woman, color=region, size=population))+
        geom_point()

```

```
Warning: Removed 22 rows containing missing values (geom_point).
```



Now, we can see more specific patterns for different regions of the world. For instance, African women tend to have more babies while European women are likely to have 2 or fewer babies. Two Asian countries, China and India (the largest dots), manage to have rather low birth rates despite their relatively low average income values.

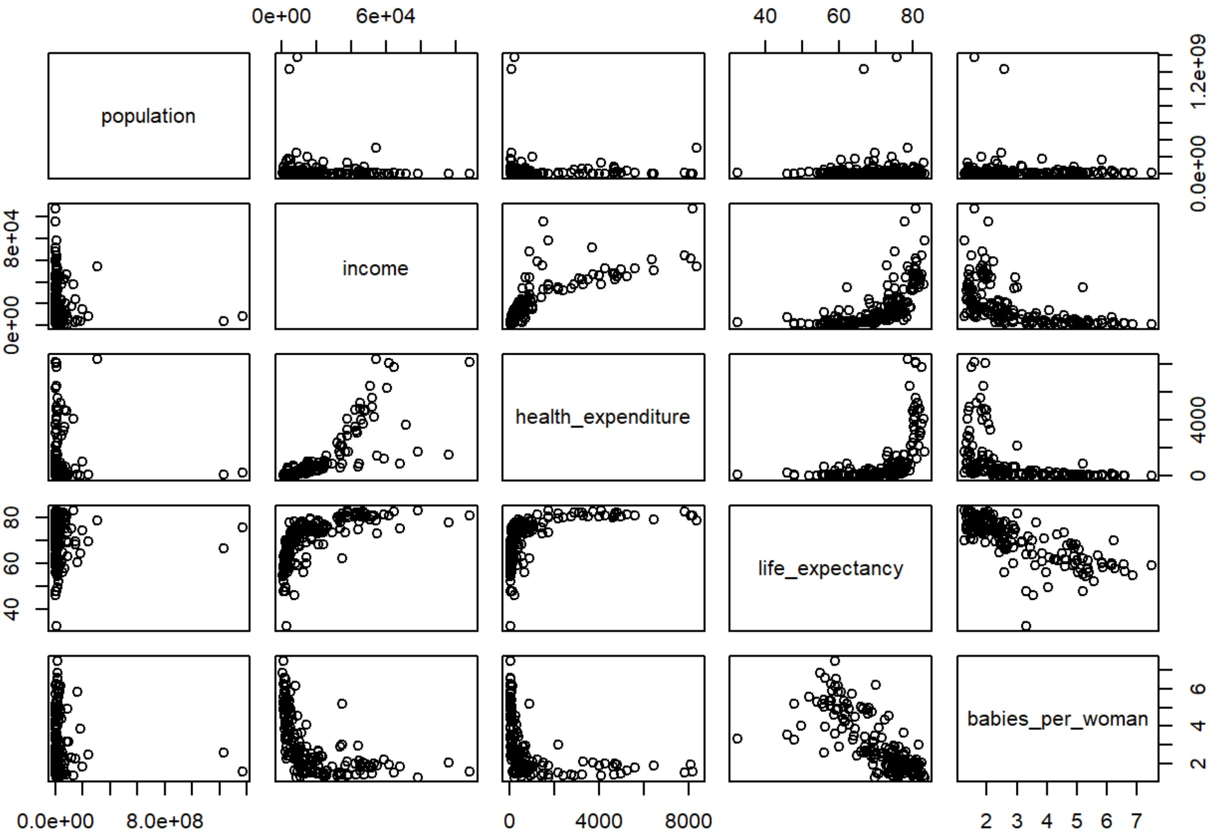
Scatterplot Matrices

For a more systematic comparison of variables, a scatterplot matrix (or a **pairs plot**) shows **all possible combinations of scatterplots** of the selected variables in a matrix-like organization. Run the following code snippet to see a scatterplot matrix of the five numerical variables in our sample dataset.

Code   Start Over   ▶ Run Code

```
pairs(world[3:7])


```

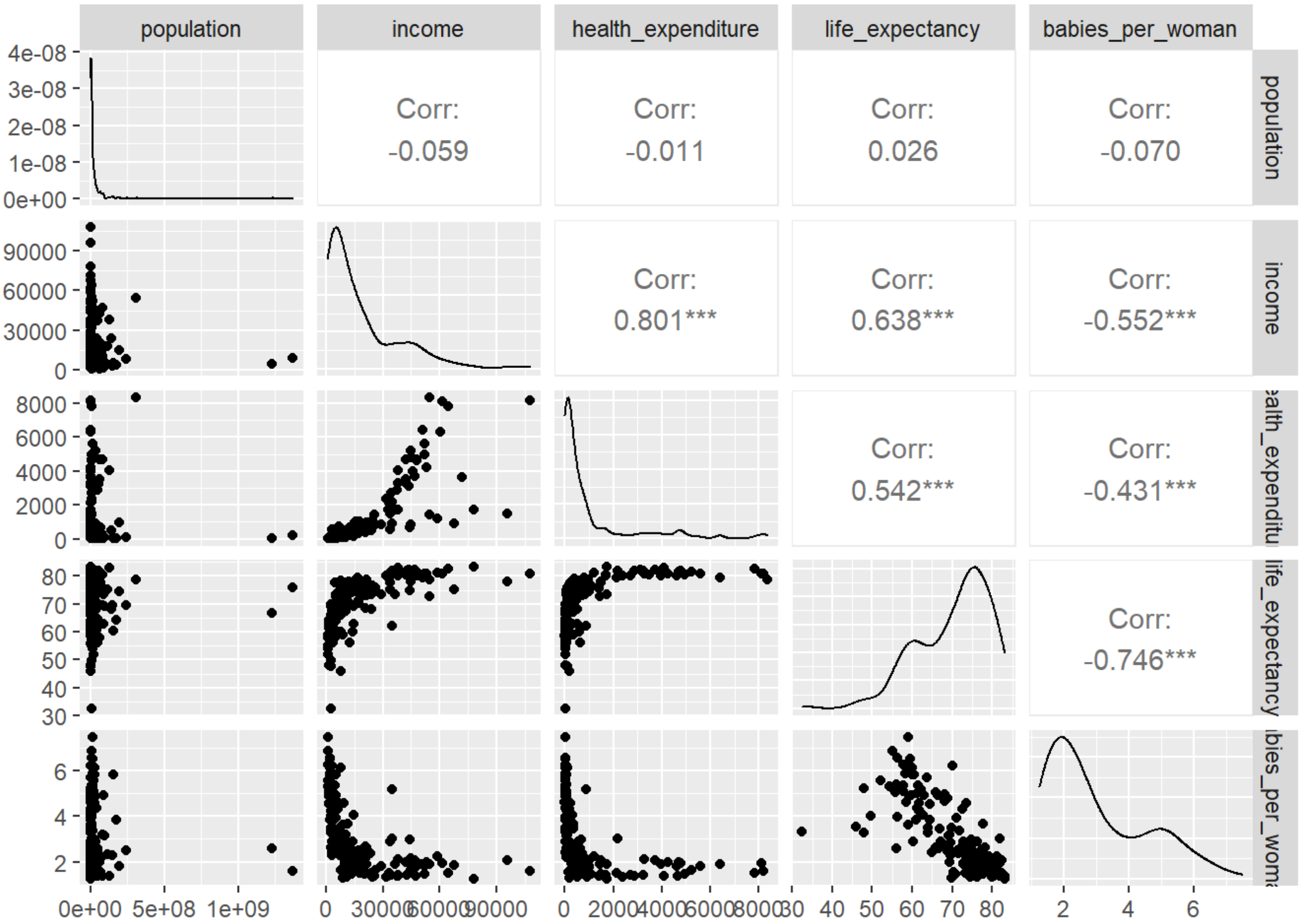


Please note that the above code block does not use *ggplot2*, but the default R diagrams. There is an obvious difference in terms of aesthetics for this plot compared to the ones you have seen above. There is not direct *ggplot2* version of this visualization, but **GGally** (https://ggobi.github.io/ggally/) extends *ggplot2* with advanced multivariate plots. The following code block uses *GGally* to draw a scatterplot matrix for the same variables.

Code   Start Over   ▶ Run Code

```
library(GGally)
ggpairs(world[3:7])

```



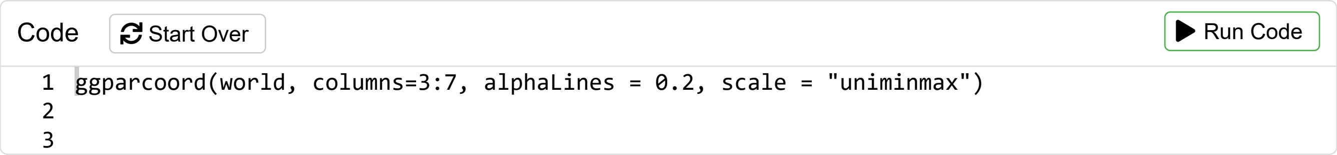
Scatterplots for each pair of variables are drawn on the left of the diagonal. The values of the *Pearson correlation coefficient*, a specific method how to calculate correlations, are shown on the right of the diagonal. The number of **asterisks** (*) marks the statisical significance of correlations and can be interpreted as a measure of certainty (not strength). The diagonal shows the univariate distribution of each variable.

Now, we can much quicker check the pairwise correlations, both visually and through the correlation coefficients. For instance, we observe a strong positive correlation (usually, > 0.75) between `income` and `health_expenditure` and an almost as strong, but negative correlation between `life_expectancy` and `babies_per_woman`. The scatterplots show in both cases potentially interesting outliers. Unfortunately, the visualization is not interactive and does not allow to directly identify the respective countries, but we can use other means to do this (for instance, sorting the tabular output).

Parallel Coordinates Plots

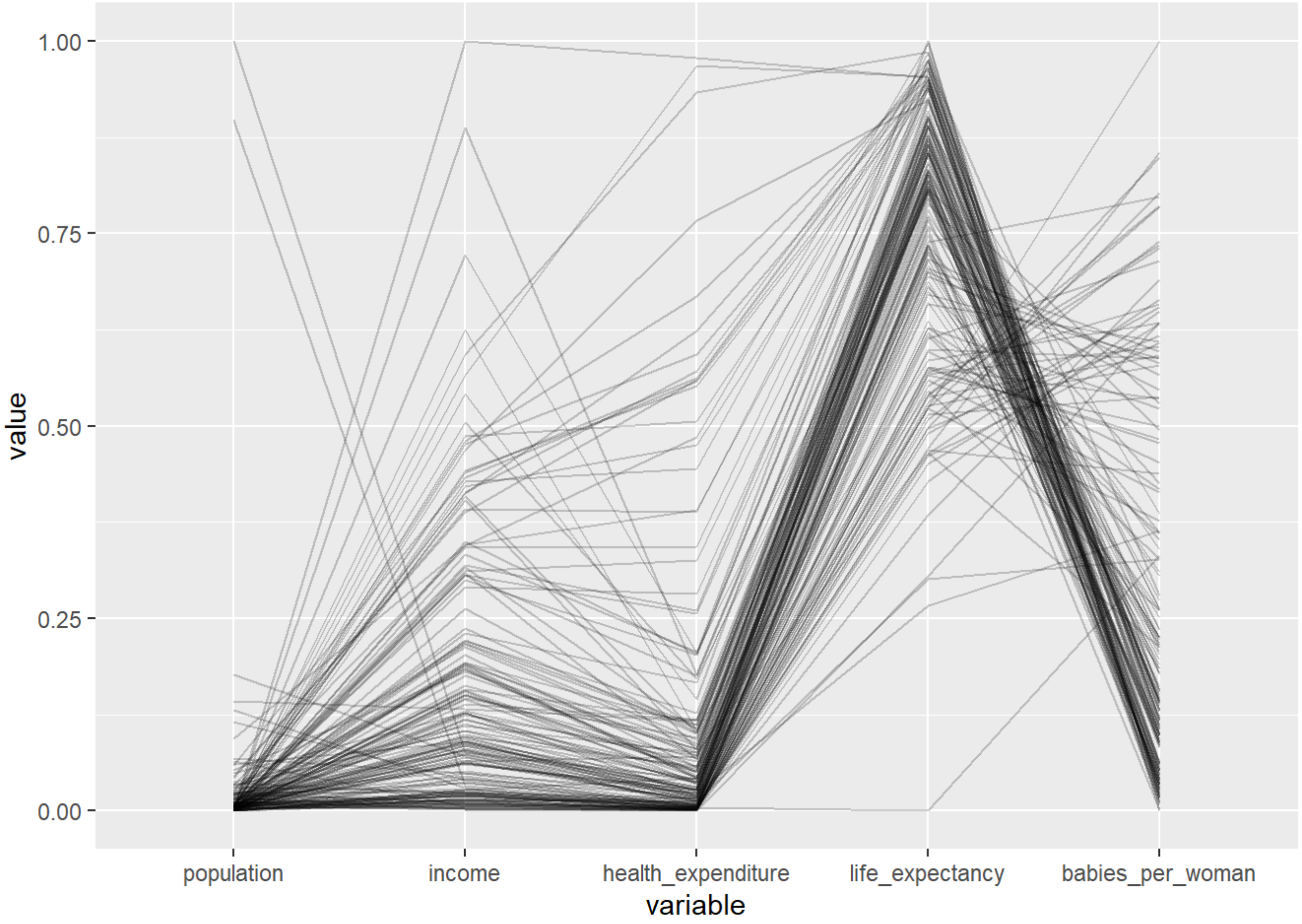
With scatterplots and scatterplot matrices, we are able to see relationships between variables and outliers as unusual combinations of values. Sometimes, also groups of similar data items appear as visual clusters. However, this is limited to two numerical variables at a time. However, specifically for detecting similar items, it is desirable to compare more than two numerical variables and see clusters or similarity within predefined groups across all these data attributes.

A parallel coordinates plot supports such comparison. Here, each variable corresponds to a vertical axis. The axes for all variables are placed in parallel and equidistant from each other. A data point is now represented as a broken line across all axes. The line intersects each axis at the respective value of the variable for the current data item. Run the following code snippet to see a parallel coordinates for our dataset where each line, hence, represents one country.



```
ggparcoord(world, columns=3:7, alphaLines = 0.2, scale = "uniminmax")


```



Once again, this implementation is based on *GGally*. We reduce the opacity of the lines (`alphaLines = 0.2`) to better see patterns in dense regions with many line crossings. For a better scaling, we use a **uni**t **min**imum and **max**imum (`scale = unitminmax`) that normalizes all axes to have a value between 0 and 1.

Now, we get an overview of all data items and all numeric variables. We can observe whether there exists a similar subset of data items regarding these attributes. For instance, we see a large group of small countries with low to medium income and health expenditure, but quite high life expectancy and middle fertility rates. Still, subtle difference are difficult to note and it remains unclear which countries belong to a specific cluster. Coloring the lines by region could maybe provide more insights.

TASK: Color the lines by variable `region` . *Hint:* You can consult the documentation (https://ggobi.github.io/ggally/reference/ggparcoord.html?q=parcoord#arguments) of `ggparcoord` .

Which is the dominant region of the cluster of countries described above?

○ Africa

○ Asia

○ Europe

○ Oceania

Submit Answer

Discussion

In contrast to visualizations like histograms and boxplots, which aggregate data, the visualization presented in this section do not aggregate data. Instead, they visualize every observation individually and patterns appear in the visual distribution of points (scatterplots) and lines (parallel coordinates plots). Scatterplots only compare two variables at a time, but can be extended to scatterplot matrices for visualization of more variables. However, these matrices are still limited to pairwise comparisons. In contrast, parallel coordinates plots literally connect more variables.

Scatterplots are particularly useful for **observing correlations between variables**. Although they do not reveal the precise extent of a correlation, they are very helpful to get a rough understanding of the correlation. This even works when the relationship is not linear (for instance, first increasing, then decreasing values as read from left to right), which common numeric correlation coefficients cannot capture. Also, deviations from the general trend can quickly be identified as outliers in these scatterplots.

Parallel coordinates plots show their strength in providing an **overview across more variables**. Clusters can be discovered by identifying density patterns in the patterns of lines. However, the resulting appearance of the plot depends on the sorting of the axes. While it is easier to see a group of items with similar values in three neighboring axes, it is much harder if these axes are scattered across other axes. Unfortunately, different patterns might require different orderings—there generally is no perfect ordering.

In our examples, we have not used **categorical variables** as axes, neither in scatterplots nor in parallel coordinates plots, but **for additional color-coding the points and lines**. This is doable for a single categorical variable. A second categorical variable can be encoded in the shape of the points or the stroke of the lines (different styles of dashing). However, this approach is limited to a few such variables, having only few categories each. Although just treating the categorical variables as numeric ones and mapping the categories to numbers is doable, this would result in scatterplots and parallel coordinates plots that are hard to interpret as proximity on the scale does no longer have a meaning.

Misinterpretation and Misuse: Scatterplots might be misinterpreted to see causation between a pair of variables that are just correlated, or intentionally misused for this. But keep in mind that **correlation does not imply causation**. Correlation is just a statistical relationship between the variable while causation relates to a phenomenon where one variable truly influences the other as an effect. Correlation can stem from a causal relationship, but might also be just a coincidence or caused by a third unseen factor. In parallel coordinates plots, **the absence of a visual cluster pattern does not imply the general absence of clusters**—axes might just need to be reordered to reveal an existing cluster or clusters are rather subtle so that they are hard to note visually.

About

This tutorial has been written by Fabian Beck and Shahid Latif, with technical support by Denis Artjuch. We thank DataCampus UDE (https://www.uni-due.de/ub/datacampus/index.php), a data literacy initiative by University of Duisburg-Essen, for partly funding the project.

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