Doing Better Data Visualization

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Abstract
Methods in data visualization have rapidly advanced over the past decade. Although social scientists regularly need to visualize the results of their analyses, they receive little training in how to best design their visualizations. This tutorial is for individuals whose goal is to communicate patterns in their data as clearly as possible to other consumers of science and is designed to be accessible to both experienced and relatively new users of R and \texttt{ggplot2}. In this article, we assume some basic statistical and visualization knowledge and focus on how to visualize rather than what to visualize. We distill the science and wisdom of data-visualization expertise from books, blogs, and online forum discussion threads into recommendations for social scientists looking to convey their results to other scientists. overarching design philosophies and color decisions are discussed before giving specific examples of code in R for visualizing central tendencies, proportions, and relationships between variables.

Keywords
graphing/plotting, data visualization, open data, open materials

Received 4/20/21; Revision accepted 8/11/21

Guiding Philosophies
This tutorial is for scientific communication. Much of what is discussed below may not apply depending on one’s goals (e.g., aesthetics) or one’s audience (e.g., children, laypersons). In this tutorial, we assume your goal is to communicate patterns in your data as clearly as possible to other consumers of science. Furthermore, we also assume some basic statistical and visualization knowledge (e.g., do not truncate your y-axis) and focus on how to visualize rather than what to visualize in a given situation.

Information richness
The first philosophy is that of richness. Edward Tufte (1983), a pioneer in data visualization, advocated as principles “Tell the truth” and “Show as much data as
possible.” Using visualizations to increase information richness speaks to both principles. Anscombe’s quartet (Fig. 1; Anscombe, 1973) is a famous illustration of how descriptive statistics can conceal important features of your data.

Every data visualization, like any descriptive statistic, is a simplification of your data. Just like descriptive statistics can mask meaningful underlying variation, basic visualizations that oversimplify your data can do so as well. To the extent that you include more fine-grained information, you can better convey the actual patterns within your data. Consider the classic bar plot: When used to summarize means, bar plots oversimplify because they depict only the means of different conditions, and a great deal of important information is lost (Weissgerber et al., 2015). For example, two conditions might have the exact same mean but very different underlying distributions of observations giving rise to those means (Fig. 2).

Including more visualization features can convey more information to the reader in the same space, thereby increasing the information richness of the visualization. A common first step would involve representing the variability around those means (e.g., error bars). A further step would be representing the distribution of...
the observations. An additional step would be visualizing the observed data points giving rise to those means and distributions. Readers would then have access to both summary statistics and the variability and shape of the entire distribution of observations, which provide greater understanding of the certainty of any estimate (Helske et al., 2021).

Of course, there is a subjective upper ceiling to how much information can be conveyed in any visualization before it instead hinders understanding. Figure 3 depicts the correlation between attractiveness and intelligence for ratings of targets across four ethnicities (represented by shapes) from participants in 11 world regions (represented by color; with data from Jones et al., 2021). This figure is too rich in information; it hinders the viewer’s comprehension of all the data presented.

Overwhelmingly complex figures impede the overarching goal of science communication: to convey information clearly. And deciding when a figure is too rich is unavoidably subjective. Yet as we discuss below, research into the amount of information understood from visualizations can inform exactly where the information richness ceiling might be, depending on the type of visual (Cleveland & McGill, 1985; Heer & Bostock, 2010).

**Minimalism**

A second important philosophy is that of minimalism. Visualizations can be evaluated in their signal-to-noise ratio, in which signal is the information being conveyed and noise is anything else. The most effective communication maximizes the signal-to-noise ratio by minimizing visual clutter that might interfere with the signal. An extreme version of this argument is that one should justify every single pixel in the visualization. Features not conveying information or allowing readers to assess the patterns more easily should be removed. These might be overlooked features included as default or commonly seen in some software packages (e.g., excessive gridlines in the plot panel). As an extreme example, the serifs in various typefaces are unnecessary pixels because they are not providing additional information. Sans-serif typefaces are more consistent with minimalism. Furthermore, it is rare that any analysis done by most social scientists requires a three-dimensional visualization because it distorts the data and hampers readers’ understanding (Wilke, 2019). Shadows or reflections under text or borders on shapes are all visual noise that is not conveying additional information. To be consistent
with the philosophy of minimalism in effective scientific communication, these unnecessary flourishes should be removed.

Color

One of the most important considerations in any modern visualization is that of color. There are a number of concerns to simultaneously navigate when considering your choice of color. The first is inclusivity. Five percent of the human population, 8% to 10% of men, have some sort of color blindness; the most common is red-green color blindness (Neitz & Neitz, 2011). Another concern is that although screen-based reading of articles is now more common, ideally your color choices would still effectively convey information when printed in grayscale because your article will likely be sometimes read in that way. Most importantly, consider the type of information being presented. Are your data categorical? Are there two categories or five? Continuous? Is there a zero point in your continuum? The answers to each of these questions should inform your palette choice.

When your data are categorical, your goal is to choose colors that are maximally differentiable within the color space (while simultaneously being safe for color blindness and gray scale). Exactly what these maximally differentiable colors might be depends on how many categories you need to be equally spaced in color. Excellent tools such as ColorBrewer (Brewer et al., 2003) palettes are valuable and available at https://colorbrewer2.org.

When considering a continuous scale, color gradients can bias a reader’s perception of relative quantitative differences. For instance, certain colors, such as yellow, can create apparent divisions in a scale not actually there because of their high luminosity. Some other color transitions can bias readers into believing there is a bigger value change in a certain part of the scale. It is important that the color gradient consistently changes in value from the top to the bottom of the scale identical to the value change of the numbers the colors represent.

Sometimes researchers may wish to visually represent a zero point along a continuous scale, such as from −3 to 3. In this situation, it is informative to have the positive and negative directions be distinct colors that scale as the values become farther from zero. In addition, the zero point may be best represented as no information, which separates the colors chosen for the positive and negative side of the scales (Fig. 4). Some ideal color palettes can again be found for this situation through ColorBrewer (Brewer et al., 2003).

Several packages in R currently represent the state of the art. One is viridis (Garnier et al., 2018). It has been carefully developed to have eight palettes that represent continuous change across a spectrum in palettes that are safe for both color blindness and gray scale (Nuñez et al., 2018). Another is the colorspace package (Zeileis et al., 2019), which is based on human color perception; colors vary along hue, chroma, and luminance dimensions. Likewise, scico (Crameri, 2018) offers gradients that are perceptually uniform and universally readable.

Better Visualization of Common Results

As a general philosophy, goal-centered graph design, or choosing a visualization that highlights your specific hypotheses or goals, will make visualizations most effective. There are some common visualizations that are overwhelmingly used to convey certain types of information. Many of these enjoy their level of popularity because of historic precedent in that area of research and perhaps at one time did comprise the cutting edge of visualization. Yet like any technology, other improved methods have been developed that are now objectively superior. Summarizing these advances very generally, the improvements in visualization hinge on providing improved methods of conveying two types of information (that are related): representations of variance around a central tendency and representations of the overall distribution of the data. In this section, we discuss three common types of information to be conveyed by studies in the social sciences and the modern best practices for conveying that information in data visualizations.

R code and example data are provided in each section. All plots were created using the ggplot2 package (Wickham, 2011), which is required for the tutorial code to run, along with data hygiene packages such as dplyr (Wickham et al., 2021). In addition, we used the viridis (Garnier et al., 2018) and colorspace (Zeileis et al., 2019) color palette libraries, ggExtra (Attali & Baker, 2019), to add marginal density plots and histograms, and ggdist (Tiedemann, 2020) to create the raincloud plots presented below. For those interested in a primer to R, the tidyverse, or ggplot2, see the For Further Reading section at the end of the article. More information on each
package is available in the Supplemental Material available online.

```r
# Required R packages
library("ggplot2") # required to make plots
library("dplyr")  # for data wrangling/hygiene
library("viridis") # viridis color palettes
library("colorspace") # colorspace color palettes
library("ggExtra") # to add marginal density plots & histograms
library("gghalfes") # required to make raincloud plots
```

In addition to loading these libraries, we set up a custom minimalism theme to reduce the redundancy in R code across our examples in the article. The R code provided in full is available as supplemental material at https://osf.io/kx4us/.

```r
# create ggplot2 theme
# we will use ggplot's minimal theme as a base and modify it to be usable across our plots
theme_minimalism <- function(){
  theme_minimal() + # ggplot's minimal theme hides many unnecessary features of plot
  theme( # make modifications to the theme
    panel.grid.major.y=element_blank(),
    # hide major grid for y axis
    panel.grid.minor.y=element_blank(),
    # hide minor grid for y axis
    panel.grid.major.x=element_blank(),
    # hide major grid for x axis
    panel.grid.minor.x=element_blank(),
    # hide minor grid for x axis
    text=element_text(size=14),
    # font aesthetics
    axis.text=element_text(size=12),
    axis.title=element_text(size=14, face="bold"))
}
```

### Central Tendency

Perhaps the most common information social scientists wish to convey are the central tendencies, usually means, in several different conditions. The most common way of representing this information is the bar plot. As alluded to above, certain variants of bar plots present only the mean, a simplification that occludes much information about the underlying data. Improved bar graphs include error bars representing variation around that mean, albeit still in a simplified fashion.

Another common index of central tendency is that of the median. A data visualization based around the median is the box plot, pioneered by Spear (1952) and enhanced into its current form by Tukey (1977). For a dated visualization, the box plot remains extremely effective in conveying a large amount of information about the underlying data. Yet modern improvements have been made.

The addition of the two additional components mentioned above, the actual observed data points and a visualization of the distribution of those points, can increase information richness. These additions far better convey the underlying data giving rise to the central tendencies.

### Raincloud plot

Here, we recommend the raincloud plot over alternatives because it best operationalizes the philosophies laid out above (Allen et al., 2019). Essentially, the raincloud plot includes a representation of the overall distribution of observations, the actual observations, and measures of central tendency. If desired, elements of the box plot could be seamlessly integrated in additional layers such that the median and the range of the quartiles of the distribution are included.

In the following example, we use a raincloud plot to illustrate Québec residents’ views on “Bill 21,” a recent law passed by the government of Québec prohibiting some public-sector employees from wearing religious symbols. We measured the extent to which Québécois believed the bill was implemented to address concerns over specific religious symbols (e.g., hijab, crucifix) on items rated on a Likert scale from 1 to 7 (Fig. 5).

Some features included above improve the visualization. With large numbers of observations, individual data points overlap. A solution we employed above, on Line 15, is to jitter the location of these data points to reduce this overlap. This slightly changes their location on the x-axis on an irrelevant y-axis so they can be observed. Enhancing this visualization further is the partial transparency of these data points on Line 16 (i.e., \( \alpha \)).
# Required packages for raincloud plots
library("readr")
library("gghalves")

load("RaincloudData.Rda")

# Raincloud plot with repeated measurements
f1 <- RaincloudData %>%
  ggplot(aes(x = ReligiousSymbol, y = Relation_to_Bill21)) +
  # Add individual observations to the plot
  geom_point(aes(color = ReligiousSymbol), position = position_jitter(width=.1), size=.5, alpha=.8) +
  # Define color palette
  scale_color_discrete_qualitative(palette="Dark 3") +
  scale_fill_discrete_qualitative(palette="Dark 3") +
  # Add the mean for each level of X
  stat_summary(fun=mean, geom="point", shape=21, col="black", fill="white") +
  # Add boxplot for observations at each level
  geom_half_boxplot(aes(fill=ReligiousSymbol), position = position_nudge(x=.15), errorbar.draw=FALSE, width=.2) +
  # Add violin plots for observations at each level
  geom_half_violin(aes(fill=ReligiousSymbol), bw=.45, position = position_nudge(x=.3)) +
  # Optional styling
  coord_flip() +
  xlab("Religious Symbol") +
  ylab("Perceived Relation to Bill 21") +
  scale_y_continuous(breaks=seq(1,7,1)) +
  theme_minimalism() +
  theme(legend.position="none")#

# save plot
ggsave(f1, filename="figs/Raincloudplot.png", dpi=300, type="cairo", height=14, width=18, units="cm")
It is our opinion that these methods of data visualization fully subsume the information conveyed by the bar plot and box plot. In fact, because we do not believe there to be any information present in the bar plot not available in its modern descendants, for representing central tendencies in finalized scientific communication, we think the bar plot should be fully retired.

**Cluster heat map**

Some researchers may wish to show mean change over time across multiple conditions or categories or as a function of some other continuous variable. When additionally incorporating time, visualizing all the observations and distributions at each point is likely too complex and visually overwhelming. It may be more effective to focus on the information you want to convey most effectively: mean change for multiple categories over time. One visualization ideal for this situation is the cluster heat map (alternatively known as a tile map or level plot; Wilkinson & Friendly, 2009). Here, means over time are represented by color, and each rectangle represents a fixed set of time. This plot enables easy comparison both across many categories and within a category.

In the following example, we use a cluster heat map (Fig. 6) to show how explicit antigay bias changed over time across each state in the United States (with data from Ofosu et al., 2019).

In general and for various reasons, we consider the raincloud plot and cluster heat map more consistent with the philosophies laid out above for conveying central tendencies than the bar plot, box plot, violin plot, beeswarm plot, bean plot, pirate plot, lollipop plot, or ridgeline plot, although some of these might still provide some advantages in niche situations.

**Proportions or Frequencies**

Another common type of information presented is that of proportions or frequencies. Unlike central tendencies, there is no variance to represent around these observed counts. Accordingly, priorities of the data visualization vary. Yet like central tendencies, scientists often wish to visually compare proportions with one another. Because multiple proportions are a percentage of some greater whole, a classic way of representing these data for comparison is a pie chart. We see pie charts (or other circular visualizations) occasionally but
load("HeatmapData.Rda")

# cluster heat map / level plot with change over time in squares
f2 <- HeatmapData %>%
  ggplot(aes(x=Year, y=State, z=Explicit)) +
  geom_tile(aes(fill = Explicit)) +
  scale_fill_continuous_sequential(palette="Inferno", name="Explicit Bias") +
  scale_x_continuous(breaks=seq(2003,2015,3)) +
  xlab("Year") +
  ylab("State") +
  ylim(rev(levels(HeatmapData$State))) +
  theme_minimalism() +
  theme(panel.grid.major.y=element_line())

# Define color palette
# For this example, we will use the "Inferno" palette from the
colorspace package

# optional styling
scale_x_continuous(breaks=seq(2003,2015,3)) +
  xlab("Year") +
  ylab("State") +
  ylim(rev(levels(HeatmapData$State))) +
  theme_minimalism() +
  theme(panel.grid.major.y=element_line())

# we can also order the y-axis another way. below is the code to sort
the States
# by their mean level of prejudice (across all years).
yaxisOrder <- HeatmapData %>%
  group_by(State) %>%
  dplyr::summarize(avgExplicit = mean(Explicit)) %>%
  ungroup() %>%
  arrange(avgExplicit)
levels(yaxisOrder$State) <- yaxisOrder$State # this creates the order
of the states

# then, we add the following to our figure to sort according to States'
# average explicit bias
f2 <- f2 +
  ylim(levels(yaxisOrder$State)) # you may ignore the warning
  that a scale for 'y' is
  ## already present. This replaces the
  existing scale.

f2

# save plot
ggsave(f2,filename="figs/levelplot.png",dpi=300,type="cairo",
  height=23,width=11.5, units="cm") # adjust dims to change
  size of cells
Fig. 6. Cluster heat map comparing values of multiple categories over time. Here, the mean values of each state and year are conveyed by color. Although color is not always ideal for presenting values (Cleveland & McGill, 1985), it is an effective option when there is a lot of information to be conveyed because it optimizes information richness. We have sorted this plot by mean prejudice, but it could also be sorted in other ways to enable specific comparisons that emphasize the authors’ points.

Bar plot

Superior alternatives to pie charts are variants of a bar plot. Although we have critiqued the bar plot for central tendencies, when comparing proportions with one another, a simple bar plot is superior because humans comprehend values represented by length well (Cleveland & McGill, 1985; Heer & Bostock, 2010). Which type of bar plot to choose depends on one’s goals and what one might wish to emphasize to readers (presumably mirroring your statistical comparisons). For example, if you wish to compare one proportion with another, separate columns aligned next to one another far more effectively convey the size of each proportion relative to one another. In Figure 7, we illustrate the proportion of responses on a Likert-type item scaled from 1 to 7 in which greater values represent greater levels of self-reported anti-Black bias made by participants in a single week (with data from Hehman et al., 2018). Because there is no residual, there is no information lost in a bar plot representing proportions or frequencies.

Stacked bar plot

For a situation akin to multiple pie charts, when not only comparisons within a cluster are important but also comparing proportions between clusters, stacked bar plots allow for efficient comparison both between bars and
within bars. Figure 8 illustrates the changing proportion of responses on the same Likert-type item scaled from 1 to 7 made by participants across 4 weeks.

**Line plot**

Like means over time, a common situation is that researchers wish to visualize how proportions change over time or as a function of some other continuous variable. Also like means over time, this is a high amount of information that can become too complex with too many separate stacked bar plots like above. Instead, line plots are an excellent choice.

In the following example, we expand on the bar-plot examples to compare the same proportions across more than 700 time points. Figure 9 illustrates the changing proportion of responses on a Likert-type item scaled from 1 to 7 made by participants across hundreds of weeks.

Again, we consider the bar, stacked bar, and line plots more consistent with the philosophies laid out above for proportions than their alternatives, including the pie chart, spider chart, radar chart, tree map, doughnut plot, area chart, stacked area plot, or steam graph, although...
some of these might still provide some advantages in niche situations.

**Relationships**

Finally, researchers often want to visualize a relationship between two or more variables, such as a correlation or regression slope. In our subjective opinions, it is for this type of visualization that social scientists have already mostly adopted best practices. We see scatterplots regularly in our respective corner of research. Nonetheless, some additions can improve the information communicated. Like means, it is important here to represent both a central tendency of the relationship and the variance around that relationship. Typically, line graphs are used to represent relationships, and like the other types of information we are covering, they can be improved by better conveying the distribution of data.

```r
# bar chart comparing proportions across multiple discrete categories (i.e., weeks)
load("BarAndLineplotData.Rda")

# optional: define custom color palette, assigning a color for each value
my.pal <- c("7" = "#403C91",
"6" = "#8B96D7",
"5" = "#DCEBF9",
"4" = "#F5F5F5",
"3" = "#F2CB89",
"2" = "#F2B552",
"1" = "#FFCB25")

# For this example, we want to compare data from weeks 1 to 4
# so we will create an index to define which groups to compare
index = c(1:4) # compare data from weeks 1 to 4
f4 <- BarAndLineplotData %>% # define dataframe
  filter(weeks %in% index) %>% # filter data by weeks variable (weeks 1-4)
ggplot(aes(x = weeks, y = percent)) + # define x,y variables
  geom_col(aes(fill = response), width = 0.7) + # add bars, set width for bars
  theme_minimalism() + # the fill variable sets the colors

# optional styling
# Define color palette
# For this example, we will use the "viridis" palette from the viridis package
scale_fill_viridis(discrete=T, option="viridis", # color of bars
  name = "Response") + # change legend title
  scale_fill_manual("Legend", values = my.pal) + # uncomment to use
  theme(panel.grid.major.y=element_line()) # show major grid for y axis
f4 # save plot
ggsave(f4, filename="figs/barplot2_stacked.png", dpi=300, type="cairo",
  height=11, width=18, units="cm")
```
Improved scatterplot

We consider the scatterplot to be superior to a line plot because it demonstrates both the relationship between variables and the underlying observations that drive that relationship. Including additional features, such as histograms or density plots of the distributions of each individual variable along the \(x\)- and \(y\)-axes, can further improve the scatterplot. Furthermore, 95% confidence intervals around the estimate of the slope might additionally be included to indicate certainty in the slope estimate that can be hard to glean from the data points themselves.

In Figure 10, we use an improved scatterplot to visualize the relationship between implicitly and explicitly measured anti-Black bias across hundreds of White participants (aggregated to geographic regions from Hehman et al., 2019). We include histograms in the margins of the \(x\)-axis and \(y\)-axis to show the underlying distributions of each variable.
Fig. 9. Frequency (%) of responses on a Likert-type item scaled 1 to 7 in which observations collected between 2007 and 2019 are compared. Rather than stacking the values, the lines are plotted over one another so their respective change over time can be compared (in contrast to a stacked area plot, which can impede the accurate perception of values; Few, 2011). We included a black line representing the total per week. The data here are proportions, so this value never deviates from 1. However, when researchers are plotting raw values or frequencies over time, it might be informative to indicate how many total observations occurred per week across all the distinct categories being plotted.

Contour plot

Sometimes researchers may have so many observations that scatterplots are no longer effective. For instance, with millions of data points, using a scatterplot results in a smear in which no pattern is discernible because of overlap of the points. There are two solutions we prefer in this situation. The first is to randomly sample a percentage of the observations and represent them in the visualization as a scatterplot. However, doing so can require some additional programming. Alternatively, researchers might employ a contour plot, essentially turning the scatterplot into a heat or topographical map in which certain colors represent a higher density of observations (i.e., a modern version of sunflowers; Cleveland & McGill, 1984), which enables readers to still ascertain the underlying relationship while simultaneously seeing the distributions of the observed data across two axes.

To illustrate, in Figure 11, we use a contour plot to represent the same data presented above: the relationship between implicit and explicit anti-Black bias. Rather than the histograms we presented above, here, as a variant, we included density distributions in the margins of the x-axis and y-axis. In fact, we prefer density distributions over histograms because we believe they are more consistent with the principle of minimalism. For consistency, we have used these same data to illustrate this type of visualization. Yet it is important to emphasize we consider contour plots more appropriate when there are more observations (e.g., > 5,000) to ensure a visualization is not too information rich.

```
194  load("ScatterPlotData.Rda")
195
196  # scatterplot
197  f6 <- ScatterPlotData %>%
198      ggplot(aes(x=ExplicitBias, y=ImplicitBias)) +
199      geom_point(size=1, alpha=.7, color="darkgray") + # define size and color
200      geom_smooth(size=1, method=lm, color="slateblue") + # method=lm indicates linear
201      scale_x_continuous(breaks=seq(0.4,1.6,.2)) + # x-axis tick marks
202      scale_y_continuous(breaks=seq(0.3,1.6,.05)) + # y-axis tick marks
203      xlab("Explicit Bias") + # x-axis label
204      ylab("Implicit Bias") + # y-axis
205      theme_minimalism() + # apply custom minimal theme
206      theme(panel.grid.major.x=element_line(),
207      panel.grid.major.y=element_line(),
208      panel.grid.minor.x=element_line(),
209      panel.grid.minor.y=element_line())
```
# contour plot with density plots in the margins
f9 <- ggPlot(ScatterPlotData %>%
  ggplot(aes(x=ExplicitBias, y=ImplicitBias)) +
  geom_point(stat="identity", size=0.01, alpha=0) +
  stat_density_2d(aes(fill=..level..), h = 0.1, geom="polygon") +
  scale_fill_viridis(option="viridis") +
  stat_smooth(method = "lm", formula = y~x, size=2, color="black", se=F) +
  opts(title="Improved scatterplot visualizing the relationship between implicit and explicit anti-Black bias, including a 95% confidence band of the slope, with histograms of the variable on each axis in the opposite margins.
# add marginal histograms (requires ggExtra package)
f6 <- ggMarginal(f6, type="histogram", fill = "lightgray", xparams = list(bins=15), yparams = list(bins=15))
# save plot
ggsave(f6, filename="figs/scatterplot.png", dpi=300, type="cairo", height=14, width=18, units="cm"

# optional styling
scale_fill_viridis(option="viridis") +
stat_smooth(method = "lm", formula = y~x, size=2, color="black", se=F) +
# color using viridis palette
# add regression line
# style of regression line
Spaghetti plot

Finally, modeling relationships in clustered data in multilevel frameworks is becoming increasingly commonplace. Although showing the grand averaged slope across all clusters is important, it is valuable to show the relationship within each cluster of the multilevel model varying around the grand slope. Effectively capturing this complexity in a single visualization is the spaghetti plot (Fig. 12). We do not recommend including 95% confidence intervals, grid lines, or underlying data points in this plot (as in Fig. 2) because it can become too informationally rich and confusing, depending on the number of clusters. Here, we visualize how attractiveness and intelligence ratings of faces correlate within participants (with data from Xie et al., 2019).

Fig. 11. Contour plot visualizing the relationship between implicit and explicit anti-Black bias, with probability density functions in the margins. Areas with higher values on the legend indicate higher density of observations.
load("SpaghettiPlotData.Rda")
# Spaghetti plot for random slopes
f7 <- SpaghettiplotData %>%
  ggplot(aes(x=attractive, y=intelligent)) +
  geom_line(aes(group=ParticipantID, color=ParticipantID),
    stat="smooth", method="lm", color="gray", size=0.8, alpha = 0.5) +
    stat_smooth(method="lm", formula=y~x, color="coral",size = 1.5,se=F) +
    coord_cartesian(ylim=c(1,7), xlim=c(1,7)) +
    xlab("Attractiveness Ratings") +
    ylab("Intelligence Ratings") +
    theme_minimalism() +
    theme(legend.position="none")
# optional styling
#scale_color_viridis(discrete=TRUE) +
coord_cartesian(ylim=c(1,7), xlim=c(1,7)) +
# set axis limits
xlab("Attractiveness Ratings") +
ylab("Intelligence Ratings") +
theme_minimalism() +
theme(legend.position="none")
# hide legend
f7
# save plot
ggsave(f7,filename="figs/spaghettiplot.png",dpi=300,type="cairo",
  height=14,width=18, units="cm")

Recommendations for Further Reading

Although we, the authors, regularly read, think about, and create data visualizations for our research, we are not visualization professionals. Here, we have attempted to distill and present what we consider the information most applicable and useful to other social scientists from people with greater expertise than we. However, we encourage interested readers to seek out the primary sources and modern practitioners and have included a section, For Further Reading, before the Reference section as a starting point.

Summary

Visualizing one’s data effectively to convey information is a science unto itself with research-informed best and worst practices. Yet this is an area in which social scientists receive little training. Here, we aimed to essentially distill advice and information scattered across data-visualization blogs, books, and Internet discussion threads into recommendations viable for individuals communicating their data and results to other consumers of science.

It is not coincidental that our recommendations often hover around the most simple: variants of the bar plot, line plot, or scatterplot. These tried-and-true methods of visualization have persisted across decades because they are effective and clear. Although new visualizations are continually being developed (e.g., beeswarm plot, steam graph), these sometimes have a goal of aestheticism and novelty involved, not clear scientific communication. Although some might envision specific scenarios in which other visualizations are superior, we believe that the recommendations and code we present above will best serve most social scientists in most common situations. We believe it is most important for researchers to keep the guiding philosophies in mind when making their unavoidably subjective decisions about which visualization might be most effective to convey understanding of their data or critical hypothesis test. We hope this tutorial aids in this endeavor.
Fig. 12. Spaghetti plot visualizing the relationship between ratings of attractiveness and ratings of intelligence made by the same observers evaluating various faces. Thicker coral line represents the grand intercept and slope across all observers. Because of the complexity of the figure, we removed features we would normally include, such as gridlines, observations, or confidence intervals of slopes. In addition, because of the multilevel nature of the data, histograms or density plots on the margins are also inappropriate (because they do not accommodate the clustering within the data).

Recommended Reading

A freely and fully available online introduction to R and the tidyverse
A freely and fully available online introduction to programming in R
A freely and fully available online introduction to ggplot2
An excellent modern resource, with some portions available online, including some code for R.
The classic text on data visualization by an initial pioneer in the area
https://www.perceptualedge.com/
A website and blog maintained by data visualization expert
Stephen Few, with numerous entries spanning back to 2006
A practical guide to data visualization. For example, see here for comparisons of differential effectiveness of ways of conveying different types of values (e.g., shapes, color, line length, position, etc): “Visual variables,” https://datavizhandbook.info/.

Transparency

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*Editor:* Daniel J. Simons

**Author Contributions**
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**Declaration of Conflicting Interests**
The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

**Funding**
This research was supported by the Fonds de Recherche (FRQ-SC NP-267701) to E. Hehman.

**Open Practices**
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Preregistration: not applicable
All data and materials have been made publicly available via OSF and can be accessed at https://osf.io/kx4us/. This article has received badges for Open Data and Open Materials. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

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**Acknowledgments**

We thank Neil Hester, Eugene Ofosu, Jennifer Suliteanu, and Chevieve Heri for feedback on an early draft.

**Supplemental Material**
Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/25152459211045334

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