Informative Data Visualization with Raincloud Plots in JASP

Vincent L. Ott[1], Don van den Bergh[1], Bruno Boutin[1], Johnny van Doorn[1], František Bartoš[1], Nicholas Judd[2], Jordy van Langen[2], Luke Korthals[1], Rogier Kievit[2], Laura Groot[1], and Eric-Jan Wagenmakers[1]

[1]Department of Psychological Methods, University of Amsterdam

[2]Donders Institute, Radboud University

Author Note

Vincent L. Ott https://orcid.org/0000-0002-1325-8006

František Bartoš https://orcid.org/0000-0002-0018-5573

Jordy van Langen https://orcid.org/0000-0003-2504-2381

Luke Korthals https://orcid.org/0009-0006-2098-8679

Rogier Kievit https://orcid.org/0000-0003-0700-4568

Eric-Jan Wagenmakers https://orcid.org/0000-0003-1596-1034

Correspondence concerning this article should be addressed to Vincent L. Ott, Department of Psychological Methods, University of Amsterdam, Nieuwe Achtergracht 129B, PO Box 15906, 1001 NK Amsterdam. E-mail: mail.vincent.ott@gmail.com

Abstract

Proper data visualization helps researchers draw correct conclusions from their data and facilitates a more complete and transparent report of the results. In factorial designs, so-called *raincloud plots* have recently attracted attention as a particularly informative data visualization technique; raincloud plots can simultaneously show summary statistics (i.e., a box plot), a density estimate (i.e., the cloud), and the individual data points (i.e., the raindrops). Here we first present a 'raincloud quartet' that underscores the added value of raincloud plots over the traditional presentation of means and confidence intervals. The added value of raincloud plots appears to be increasingly recognized by cognitive psychologists: a focused literature review shows that the prevalence of raincloud-style plots in *Psychonomic Bulletin & Review* has risen from 2% in 2013 to 37% in 2023. To further encourage this trend and make raincloud plotting easy and practical for a broader group of researchers and students, we have recently implemented a comprehensive suite of raincloud plots in JASP. Examples from two factorial research designs illustrate how these raincloud plots support a correct and comprehensive interpretation of the data.

Keywords: Anscombe's quartet, good research practices, statistical software

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Graphical output [. . .] is readily available to anyone who does [their] own programming. [. . .] Unfortunately, most persons who have recourse to a computer for statistical analysis of data are not much interested either in computer programming or in statistical method, being primarily concerned with their own proper business. Hence the common use of library programs and various statistical packages. Most of these originated in the pre-visual era. The user is not showered with graphical displays. He can get them only with trouble, cunning and a fighting spirit. It's time that was changed.

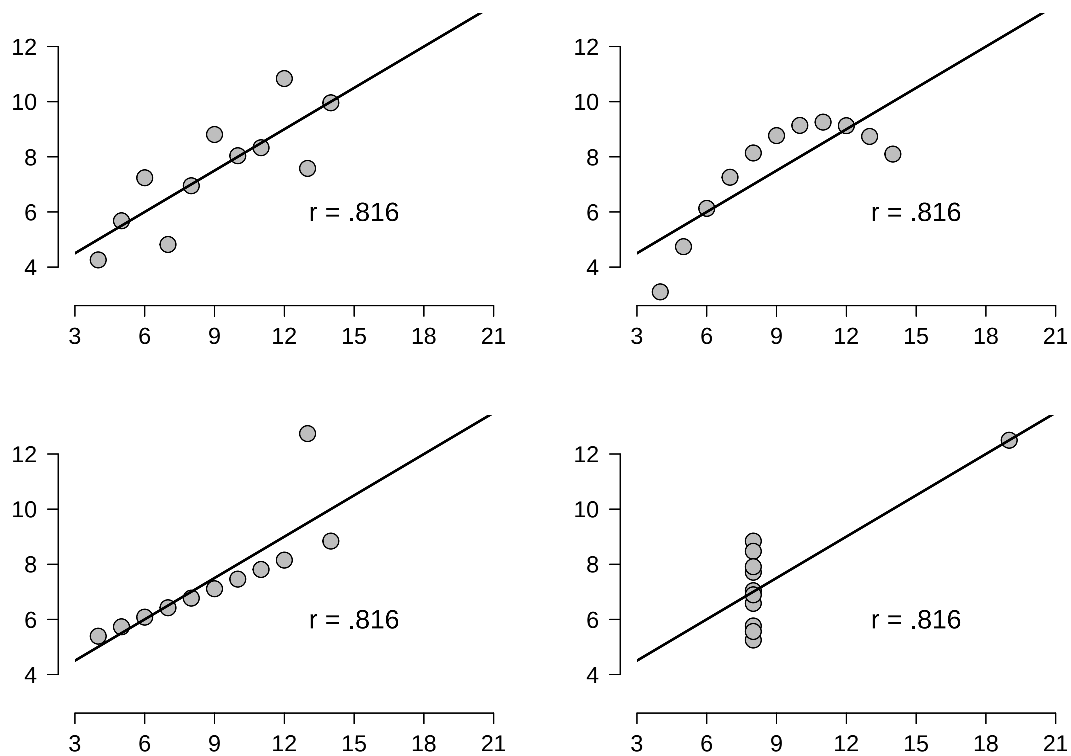
Anscombe, 1973

Data visualization is crucial for a correct and complete understanding of both experimental and observational data (e.g., Tukey, 1972, 1977). Students who take courses in data analysis are traditionally confronted mostly with the fundamentals of statistical modeling, and this may create the temptation to apply the statistical models thoughtlessly, under the untested assumption that summary statistics paint a complete picture of the underlying data.

The pitfalls of relying exclusively on summary statistics are aptly illustrated by 'Anscombe's quartet' (Anscombe, 1973) shown in Figure 1. The quartet consists of four scatter plots, each comprised of 11 pairs of observations. The observations have been constructed such that key summary statistics are identical across the four plots; specifically, in each scatter plot the two variables x and y have the same sample mean (i.e., $\mathrm{M}_x = 9.00$ and $\mathrm{M}_y = 7.50$, respectively) and the same sample standard deviation (i.e., $\mathrm{SD}_x = 3.32$ and $\mathrm{SD}_y = 2.03$, respectively). Moreover, the Pearson sample product-moment correlation coefficient equals $r_{xy} = .816$ in all four panels, suggesting a strong positive relationship between the two variables (cf. Figure 1 in van Doorn et al., 2021). However, a mere glance at the four scatter plots reveals that the inference is valid only for the scatter plot from the top-left panel, where the observations appear randomly dispersed around the linear regression line.

Figure 1

Anscombe's Quartet Highlights the Importance of Data Visualization for Correlations. Conclusions Based on the Pearson Product-Moment Correlation are Meaningful Only for the Top-Left Scatter Plot. Figure created using R code from Wagenmakers and Gronau (n.d.).



In the top-right panel, the relation is quadratic; in the bottom-left panel, an otherwise perfect linear relation is perturbed by a single outlier; and in the bottom-right panel, another outlier drives the entire effect. Anscombe's quartet shows that it is hazardous –perhaps even reckless– to draw conclusions about correlations without visually examining the scatter plot first.

In general, data visualization allows researchers to confirm that their conclusions do not hinge on a seriously misspecified statistical model. Data visualization is also an essential element of a comprehensive and transparent research report, simultaneously generating trust and inviting appropriate scrutiny from the academic community.

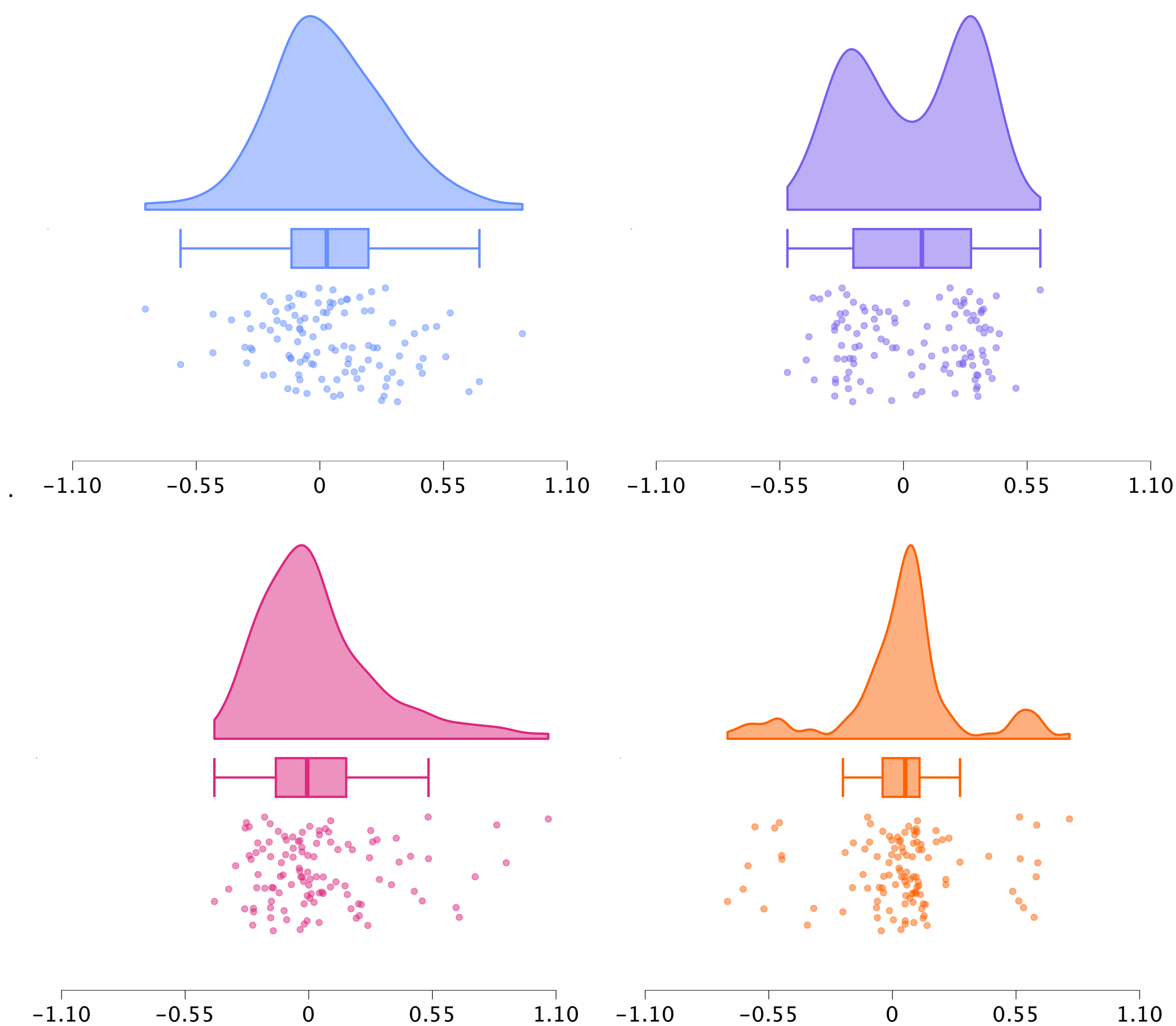
In cognitive psychology, the primary concern often lies not so much with correlations between two continuous variables but with possible changes in a dependent variable across conditions or groups. For such factorial research designs, a data visualization method that has recently attracted attention is the raincloud plot (Allen et al., 2021). The essential element of the raincloud plot is that it shows the individual observations (i.e., as raindrops). At the same time, the raincloud plot also shows a density estimate of the entire distribution (i.e., as the cloud itself), and summary statistical information as conveyed by a box-and-whiskers plot. Together, raincloud plots provide a complete overview of the data and accommodate "inference at a glance".

To underscore the importance of data visualization for factorial designs and highlight the conceptual similarity with Anscombe's demonstration for correlations, Figure 2 presents a raincloud quartet[1] (cf. Figure 1 in Stuart et al., 2024). Crucially, the data in each of the four panels of the raincloud quartet were created such that popular sample statistics are identical. Specifically, in each of the four panels, the sample mean equals M = 0.04 and the sample standard deviation equals SD = 0.27; together with a sample size of N = 111 this implies that in each panel, a one-sided one-sample t-test yields the exact same inference; a frequentist analysis shows the result to be statistically significant (i.e., $t(110) = 1.67$, $p = .049$; 95% CI for Cohen's δ = [-0.03, 0.35]), whereas a default Bayesian analysis yields $\text{BF}_{0+} \approx 1.31$, indicating that the data are slightly more likely under the null hypothesis than under the alternative hypothesis in which effect size δ is assigned a positive-only Cauchy distribution with scale parameter of 0.707 (cf. Jeffreys, 1961; Ly et al., 2016; Wagenmakers and Ly, 2023).

[1] This raincloud quartet was created via simulated annealing (Matejka & Fitzmaurice, 2017) and with help of the `R` packages `moments` (Komsta & Novomestky, 2022) and `mousetrap` (Wulff et al., 2023), the work by Blanca et al. (2013) and Freeman and Dale (2013), and ChatGPT (Brown et al., 2020).

Figure 2

A Raincloud Version of Anscombe's Quartet Highlights the Importance of Data Visualization for Factorial Designs. Figure from JASP (JASP Team, 2024)



However, as is the case for Anscombe's quartet, the inference is only meaningful for the data from the top-left panel, where the data are approximately normally distributed. In contrast, the data from the top-right panel are bimodal, the data from the bottom-left panel are right-skewed, and the data from the bottom-right panel are riddled with outliers. The raincloud plots reveal these qualitative differences immediately, preventing researchers from drawing conclusions that are evidently inappropriate, as these depend on a seriously misspecified statistical model.

We believe that raincloud plots facilitate a comprehensive and transparent analysis of data from factorial designs. Below we first present the results of a focused literature review which shows that raincloud plots are increasingly popular in cognitive psychology.

Raincloud Plots are on the Rise in Cognitive Psychology

Raincloud plots have been introduced relatively recently (i.e., in preprint form: Allen et al., 2018; though see Figure 2.4 in Ellison, 1993, for a raincloud-similar plot) and therefore do not yet feature in reviews concerning the types of plots used in the empirical sciences (e.g., Riedel et al., 2022; Weissgerber et al., 2015, 2019). In order to quantify the extent to which raincloud plots are gaining traction in experimental cognitive psychology, we considered all Brief Reports published in the 2013 and 2023 volumes of *Psychonomic Bulletin & Review*.[2] In the initial stage, the first author rated for each Brief Report ($N_{2013} = 121$ and $N_{2023} = 133$) whether or not the associated data could have been presented as a raincloud plot. Generally, this is possible if the data are continuous and originate from a factorial design. In 2013 and 2023, 82% (i.e., 99/121) and 79% (i.e., 105/133) of the Brief Reports contained data suitable for raincloud plotting, respectively. From this suitable set of articles, actual data were plotted in 82% (81/99) of the cases in 2013, and 90% (94/105) in 2023. These then form the relevant subsets of Brief Reports (i.e., a plot is presented, and it could have been a raincloud plot) for which the first author evaluated the different plot types. When an article contained multiple plots, the plot was evaluated that most closely resembled a raincloud plot. Thus, a single plot was evaluated for each Brief Report.

[2] No other volumes or journals were assessed.

Table 1

Raincloud Plots are on the Rise. Plot Types from $N_{2013} = 81$ *and* $N_{2023} = 94$ *Psychonomic Bulletin & Review Brief Reports with Raincloud-plottable Data*

	Plot Type					
Year	Bar	Box	Point	Line	**Raincloud**	**R-Similar**
2013	53% (43)	1% (1)	5% (4)	38% (31)	—	2% (2)
2023	48% (45)	1% (1)	3% (3)	11% (10)	9% (8)	29% (27)

Note. Percentages for 2013 (2013) sum to 99% (101%) due to rounding. Point = plotted means as points (i.e., bar plot without bar). R-similar = presents individual observations (i.e., the raindrops) but does not comprise all three elements of a raincloud plot.

The results of the focused literature review are presented in Table 1. In both 2013 and 2023, bar plots are relatively popular and occur in about half of the relevant cases, echoing results from other academic disciplines (Riedel et al., 2022; Weissgerber et al., 2015, 2019). Of interest here is the prevalence of raincloud plots. In 2013, not a single Brief Report presented a raincloud plot – this is not surprising, since raincloud plots were introduced only in 2018. However, in 2013 we nonetheless identified two Brief Reports that presented a plot that is similar to a raincloud plot in the sense that it shows the individual data points (i.e., the raindrops) as well as group-level information. In general it is evident that in 2013, plotting practice for factorial designs reported in *Psychonomic Bulletin & Review* was dominated by bar plots and line plots. In 2023 this plotting practice has undergone a dramatic transformation, with 37% (35/94) of relevant Brief Reports presenting either a complete raincloud plot or a raincloud-similar plot that displays the individual observations. Examples of the latter include a bar plot with raw data points or a point plot with lines that connect individual observations across conditions.

In sum, the data from Table 1 show that raincloud plots and similar plot types have risen from obscurity to popularity in less than a decade. Raincloud plots are also beginning to appear in popular statistics course books, further stimulating their adoption (e.g., Field et al., in press)

Raincloud Plots in JASP: Easy and Informative

Raincloud plots visualize data in a transparent and informative way and thus constitute a building block of good research practices. To facilitate their widespread use, raincloud plots should be easy to create. However, up until recently raincloud plots required considerable programming expertise and effort to produce (Allen et al., 2021; Judd et al., 2024; Min & Zhou, 2021; Poggiali et al., 2024). These programming demands therefore create a hurdle for researchers and students who are lacking either in programming knowledge or in the time they have at their disposal.

These hurdles can be overcome through a software program equipped with a graphical user interface (GUI). The GUI presents a convenient and efficient way to plot without programming. For example, a GUI allows teachers to include raincloud plots in their teaching even when students have different levels of programming expertise; teachers can focus on the plots without having to explain the programming commands. Moreover, even researchers with considerable programming expertise may find that working with a GUI greatly enhances their efficiency (i.e., the GUI allows an aesthetically pleasing raincloud plot to be produced with a handful of mouse clicks, without having to track down old code and debug new code).

Several GUI-based web applications have been created to produce raincloud plots (i.e., SuperPlotsOfData[3] by Goedhart, 2021; raincloudplots[4] & Raincloud-shiny[5] by Allen et al., 2021), but these lack the functionality to create raincloud plots for a wide range of different scenarios. In addition, the raincloud GUI should ideally be embedded in a software environment that also supports other statistical activities.

[3] https://huygens.science.uva.nl/SuperPlotsOfData/

[4] https://lcdlab.shinyapps.io/raincloudplots-shiny/

[5] https://shiny.hiplot.cn/raincloud-shiny/

In order to facilitate the broader adoption of raincloud plots, we have now made them easy to produce via the GUI in JASP (JASP Team, 2024). While limited raincloud plotting had been possible in JASP for some time (Lüken, 2021), JASP now has a designated, comprehensive module to create raincloud plots for a wide range of scenarios. For instance, the JASP raincloud plots can visualize up to two factors and one additional covariate that may be continuous or discrete. Means and different uncertainty intervals can be added to the plots. In repeated measures designs, individual trajectories can be shown. The JASP raincloud plots come with nine color palettes and allow the specification of custom colors. Moreover, virtually all plot elements can be fine-tuned for a finishing touch (e.g., element size, distance between elements, or axes). Finally, a table provides key statistics such as sample sizes and group medians.

In the following, we present several examples for two popular factorial designs in experimental psychology that illustrate how the JASP raincloud plots encourage both transparent reporting and meaningful inference. As supplementary material, we offer an extensive YouTube tutorial together with the corresponding JASP files (including the data) that demonstrate how to create the plots presented below.

The following software was instrumental for implementing raincloud plots in JASP: `R` (R Core Team, 2023), `ggplot2` (Wickham, 2016), `ggrain` (Judd et al., 2024), `dplyr` (Wickham et al., 2023), `ggpp` (Aphalo, 2024), and `ggtext` (Wilke & Wiernik, 2022).

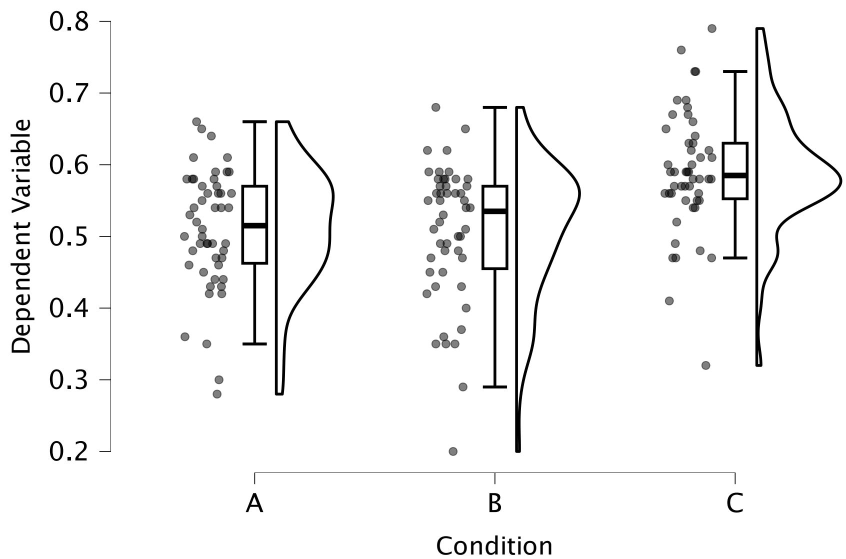
Example 1: Between-Participant One-Way ANOVA

For the first example, we simulated data in a between-participant one-way Analysis of Variance (ANOVA) design with three levels: Condition A, Condition B, and Condition C. Each condition features N = 50 participants that each yield a score on a dependent variable, for a total of $3 \times 50 = 150$ observations in the design.

A standard black and white raincloud plot of the synthetic data is shown in Figure 3. Unlike the horizontal Raincloud Quartet (cf. Figure 2), these rainclouds are now oriented vertically. Figure 3 provides an initial impression of the data: The dependent variable seems about equal in Conditions A and B. In Condition C, it seems a little higher. Furthermore, the plot reveals that the dependent variable is approximately normally distributed in each group. Finally, Condition B and C each have a single observation that is notably low and might be classified as an outlier (for a Bayesian approach to outlier handling see Godmann et al., 2024).

Figure 3

Standard Descriptive Raincloud Plot of Synthetic Data from a Between-Participant One-Way ANOVA Design with Three Levels



Note. N = 50 per condition. Figure from JASP (JASP Team, 2024).

To test the differences between the three conditions, we conducted a default Bayesian ANOVA (Rouder et al., 2012) in JASP (JASP Team, 2024; van den Bergh et al., 2020) where the prior Cauchy distribution on the fixed effects has a scale value of 0.5 (Wagenmakers et al., 2018). The resulting Bayes factor equals $\mathrm{BF}_{10} = 5866.51$ which indicates extreme evidence in favor of a main effect (Jeffreys, 1961; Lee & Wagenmakers, 2013). Post-hoc comparisons between the three conditions revealed moderate evidence against a difference between Condition A and B, $\mathrm{BF}_{01} = 4.62$, but extreme evidence that Condition C is higher both than Condition A, $\mathrm{BF}_{10} = 1726.36$, and than Condition B, $\mathrm{BF}_{10} = 1205.80$ (Jeffreys, 1961; Lee & Wagenmakers, 2013).[6]

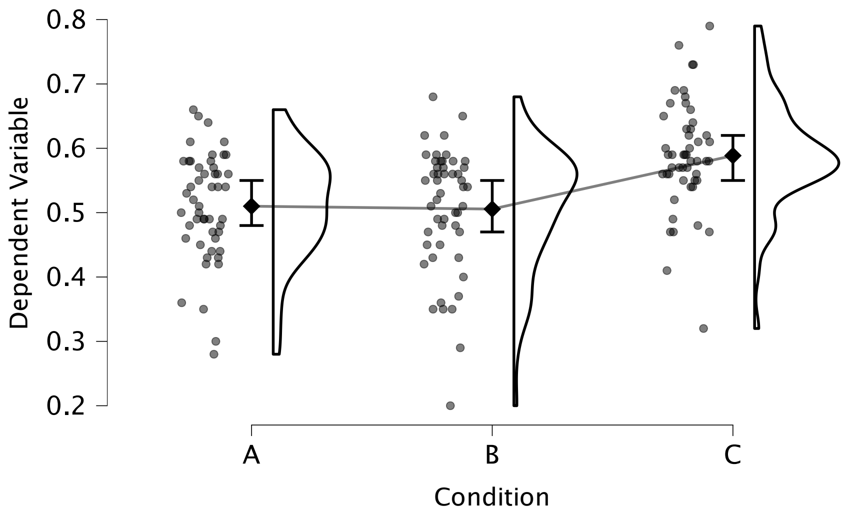
In order to add inferential content, the descriptive raincloud plot from Figure 3 can be modified to produce Figure 4. This figure shows the sample mean of each condition instead of a box plot, as well the 95% credible interval of each mean based on the statistical model that underlies the Bayesian ANOVA.[7] Each interval can be manually specified, which allows the flexible visualization of inference from various statistical models and in combination with other software (e.g., an Analysis of Covariance in JASP). Finally, the sample means are connected via lines to facilitate a visual comparison between the means for the dependent variable across the three conditions.

[6] Corrected for multiple testing (Westfall et al., 1997), the prior probability of .37 for a difference between any two conditions thus changes. It becomes less probable that conditions A and B differ (posterior probability = .12), but highly probable that Condition C is higher than Condition A and B (both posterior probabilities near 1).

[7] If desired, frequentist confidence intervals can also be displayed.

Figure 4

A Raincloud Plot of Synthetic Data from a Between-Participant One-Way ANOVA Design with Three Levels, Emphasizing the Change in Means Across Conditions by Including Inferential Content

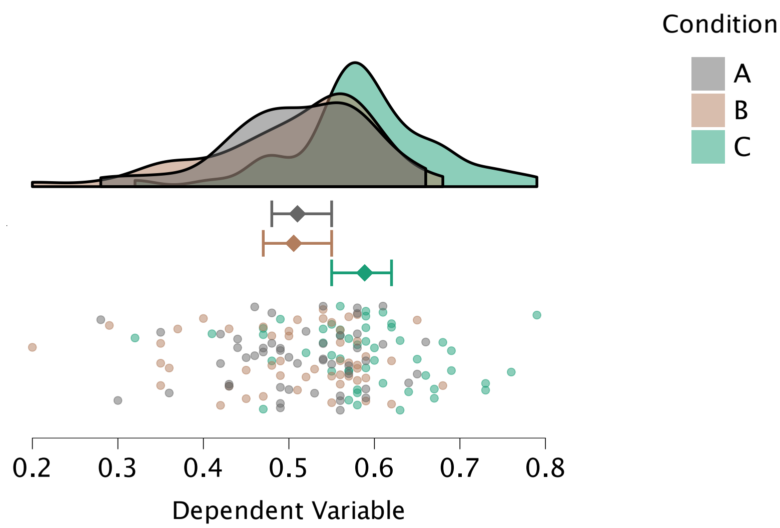


Note. N = 50 per condition. Intervals around sample means show 95% credible intervals. Figure from JASP (JASP Team, 2024).

In the present scenario, the effect size is difficult to interpret from Figure 4 alone. To facilitate the interpretation of effect size, the rainclouds can also be plotted horizontally, as overlapping densities with color coding. The resulting plot is shown in Figure 5. This overlapping raincloud plot emphasizes the difference in the credible intervals between Conditions A and B versus Condition C. Further, compared to Conditions A and B, the density estimate for Condition C is shifted to the right. The data are now visualized in a transparent and informative way that encourages researchers to interpret the size of the effect (Cumming & Calin–Jageman, 2024). In this specific scenario, the means (standard deviations) of the conditions are $M_A = .51$ (.08), $M_B = .51$ (.10), and $M_C = .59$ (.09). Thus, the mean of Condition C is about one standard deviation greater than that of Conditions A and B. According to Cohen (1992) this is a large effect.

Figure 5

An Overlapping Raincloud Plot of Synthetic Data from a Between-Participant One-Way ANOVA Design with Three Levels, Emphasizing Effect Size

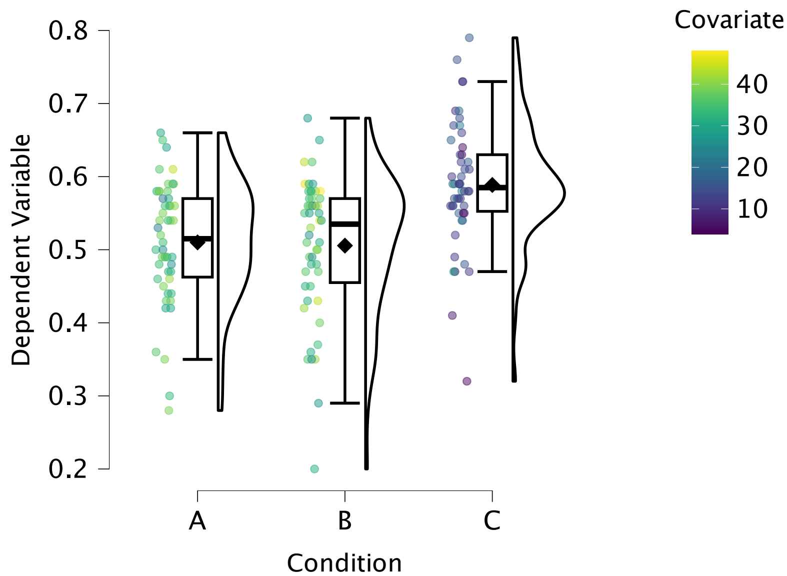


Note. N = 50 per group. Intervals around means show 95% credible intervals. Figure from JASP (JASP Team, 2024).

The data set also comprises a continuous covariate that we have not considered so far. This continuous variable can be visualized in the raincloud plot by color coding. The resulting plot is shown in Figure 6, which uses the standard raincloud representation but with the sample mean added. The plot provides two insights. First, observations beyond the box whiskers match their respective groups in regard to the covariate. In other words, the covariate does not offer a visually compelling explanation for why certain observations are suspiciously low or high. This might not be the case in other scenarios and should be explored. Second, the observations in Condition C have lower values of the covariate compared to Conditions A and B. This can be highly problematic as the difference between the conditions may be caused by changes in the covariate (i.e., the covariate is a confounding variable). This illustrates how a raincloud plot can protect researchers against premature conclusions.

Figure 6

Descriptive Raincloud Plot of Synthetic Data from a Between-Participant One-Way ANCOVA Design with Three Levels and a Confounding Covariate



Note. N = 50 per condition. Figure from JASP (JASP Team, 2024).

Example 2: Mixed 2×2 ANOVA

For the second example, we use an adjusted subset of the synthetic data presented by Judd et al. (2024).[8] These data concern the growth of sepal width for two species of flowers –versicolor and virginica– measured at two different points in time, before and after fertilizer treatment. This example was inspired by the iris data set (Anderson, 1935, as cited in Fisher, 1936). Specifically, in the hypothetical setup an experimenter starts by measuring sepal width of 50 versicolor flowers and 50 virginica flowers; these constitute the data before the treatment. Next the experimenter applies a fertilizer; after some time has passed, the sepal width for each of the 100 flowers is then measured again; these measurements constitute the data at after the treatment. In other words, each flower receives the fertilizer (the within-flower factor 'Fertilizer Treatment') but there are two

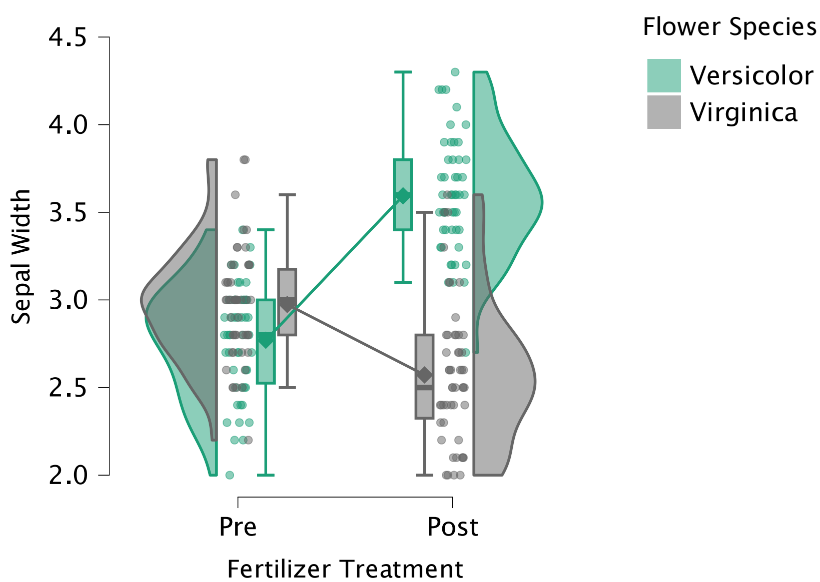
[8] See the vignette at https://cran.r-project.org/web/packages/ggrain/vignettes/ggrain.html.

separate species of flower (the between-flower factor 'Flower Species').

The fertilizer data are displayed as a raincloud plot in Figure 7. The plot emphasizes the mean change in sepal width for the two species and combines several features of the plots that were shown so far. The means and boxes are in the center of the plot and are connected via lines. The points and density estimates, on the other hand, are positioned on the outer sides so as to not overlap with the lines. The plot suggests the presence of an interaction in the sense that the fertilizer *increases* the sepal width of versicolor flowers but *decreases* it for virginica flowers (we will not test this hypothesis statistically here). In addition, Figure 7 shows that many observations share exactly the same value, suggesting that the data may have been obtained using a coarse, discrete-value measurement instrument.

Figure 7

Raincloud Plot of Synthetic Data Suggesting that Fertilizer Increases the Sepal Width of Versicolor Flowers but Decreases it for Virginica Flowers

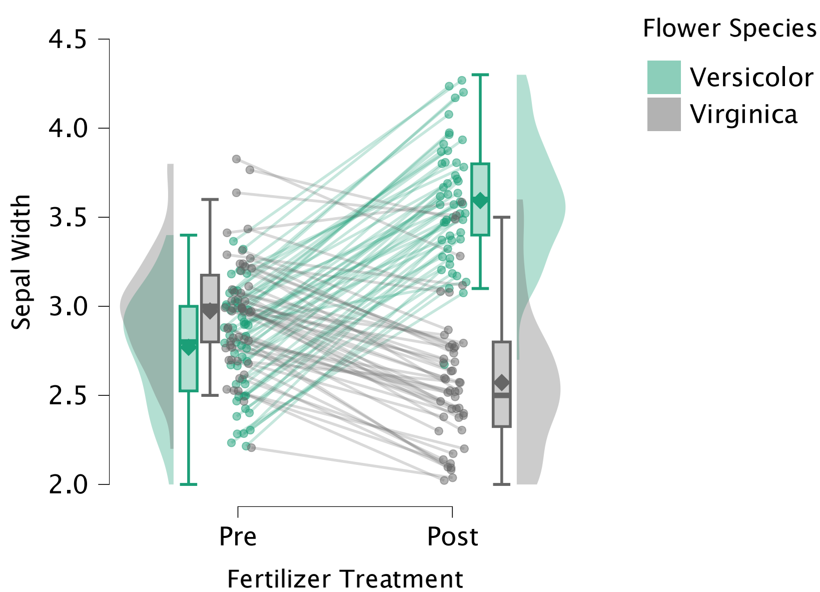


Note. $N_{versicolor} = 50$, $N_{virginica} = 50$. Figure from JASP (JASP Team, 2024).

Finally, Figure 8 presents a variation on Figure 7, the main change being that lines connect the consecutive measurements for each flower. These individual trajectories highlight the fact that the interactive pattern for the group means also holds for the majority of the individual flowers. The individual data points are slightly jittered from their true sepal width values in order to reduce the visual overlap and allow for an easier discrimination. The means and boxes are now positioned further out so as not to overlap with the lines in the center. Also, to draw attention to the individual observations in the center, the opacity of the densities and boxes is decreased and the outlines of the densities are removed. Because Figure 8 focuses on the change for individual units, this general type of plot may be particularly informative for hierarchical models that feature random effects in participants and items.

Figure 8

Raincloud Plot of Synthetic Data Emphasizing that the Interaction Effect for the Means also Holds for the Vast Majority of the Individual Flowers



Note. $N_{versicolor} = 50$, $N_{virginica} = 50$. Points are slightly jittered from their true sepal width values to better discriminate individual flowers. Figure from JASP (JASP Team, 2024).

Concluding Comments

Raincloud plots (Allen et al., 2021) allow researchers to visualize and report their data in a comprehensive fashion that goes substantially beyond the standard bar plots and line plots. A focused literature review of Brief Reports from *Psychonomic Bulletin & Review* revealed that the proportion of raincloud-like plots has risen from 2% in 2013 to 37% in 2023, a remarkably steep increase in popularity. In order to make the advantages of raincloud plots available to a wider audience, we implemented a comprehensive suite of raincloud plotting options in JASP (JASP Team, 2024). Examples from two popular factorial designs underscored the added value of raincloud plots for exploring, analyzing, and reporting empirical data.

A future avenue of raincloud plotting could be their comprehensive adaptation to dependent variables that are discrete rather than continuous (e.g., the likert-data plots in Hoogeveen et al., 2023). It should be kept in mind that raincloud plots might not always be the best choice: if a design has factors with many levels (e.g., a 6×4 design), then the different raincloud elements might clutter the plot and obscure the central findings that researchers wish to communicate. Nevertheless, even in such cases, raincloud plots could still be useful for initial data exploration.

When researchers decide to adopt a specific data visualization tool, we believe that their choice should be dictated by the science rather than the software. With the JASP GUI it is now easy to create raincloud plots, and this means researchers can make a conscious choice whether or not to report them. Until recently, students and researchers who lacked either time or programming expertise could get raincloud plots with “trouble, cunning and a fighting spirit”. With the recent implementation of raincloud plots in JASP, this has finally changed.

Declarations

We declare our involvement in the open-source software package JASP (JASP Team, 2024), a non-commercial, publicly funded effort to make statistics accessible to a

broader group of researchers and students. We have no financial or proprietary interests in any material discussed in this article.

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Conflict of interest. We have no conflicts of interest.

Ethics approval. Not applicable.

Consent to participate. Not applicable.

Consent for publication. Not applicable.

Data, Code, Analyses, and YouTube Tutorial

All data, code, and JASP files can be found at https://osf.io/mh2ka/?view_only=b87b620f056f4143b550c62e154195d4. A 86-minute YouTube tutorial on how to create raincloud plots in JASP can be found at https://www.youtube.com/watch?v=AAdXUAl_w6E.

Authors´ Contributions per the CRediT System (Brand et al., 2015) and Acknowledgments

Vincent L. Ott: Conceptualization, Methodology, Software, Formal Analysis, Investigation, Data Curation, Writing — Original Draft, Visualization.

Don van den Bergh: Software, Validation, Writing — Review & Editing, Supervision.

Bruno Boutin: Software.

Johnny van Doorn: Software, Validation.

František Bartoš: Validation, Writing — Review & Editing.

Nicholas Judd: Conceptualization, Software.

Jordy van Langen: Conceptualization, Software.

Luke Korthals: Writing — Review & Editing.

Rogier Kievit: Writing — Review & Editing.

Laura Groot: Writing — Review & Editing.

Eric-Jan Wagenmakers: Conceptualization, Validation, Resources, Writing — Review & Editing, Supervision, Project Administration, Funding Acquisition.

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