



Data visualization: From quality assurance to final publication.

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<https://github.com/keithlohse/ASNR>

Road Map

- General principles of data visualization.
 - Save yourself a lot of time with reproducible, code based graphics.
- Visualizing discrete data.
 - Special considerations for repeated measures data.
- Visualizing continuous data.
 - Special considerations for time-series data.

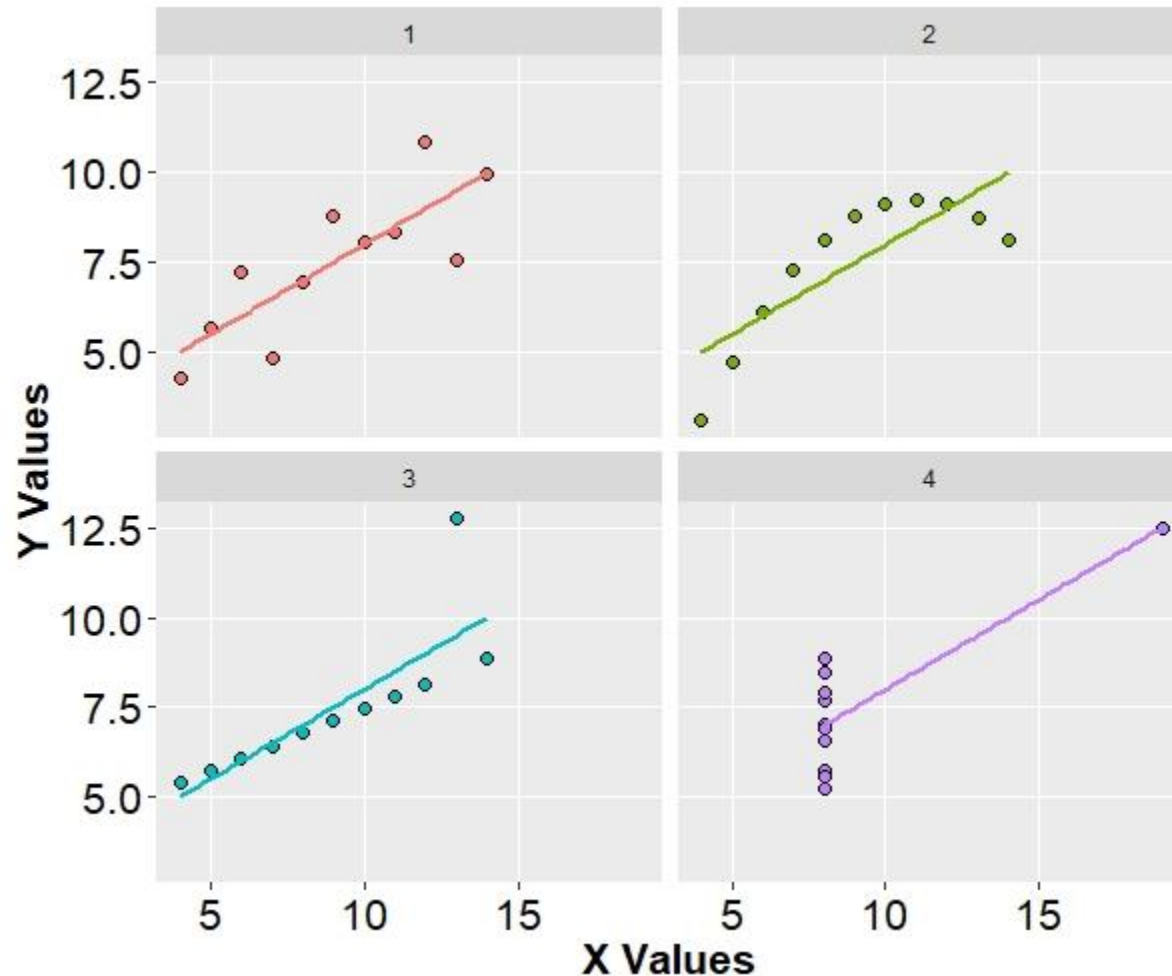
General Principles of Data Visualization



Why is visualizing data so important?

- Let's say I run an analysis in my stats program regressing Y onto X.
 - The **Intercept** is 3.00 and statistically significant.
 - The **Slope** is 0.50 and statistically significant.
- Is it fair to assume that a 1-unit change in X leads to a 0.5-unit change in Y in an approximately linear relationship?

Why is visualizing data so important?



- All of these datasets have identical slopes, intercepts, and p-values.
- **Model 1** is the only one that meets all the assumptions of linear regression.
 - 2 = nonlinear.
 - 3 = non-constant error variance.
 - 4 = extreme leverage (Cook's distance).

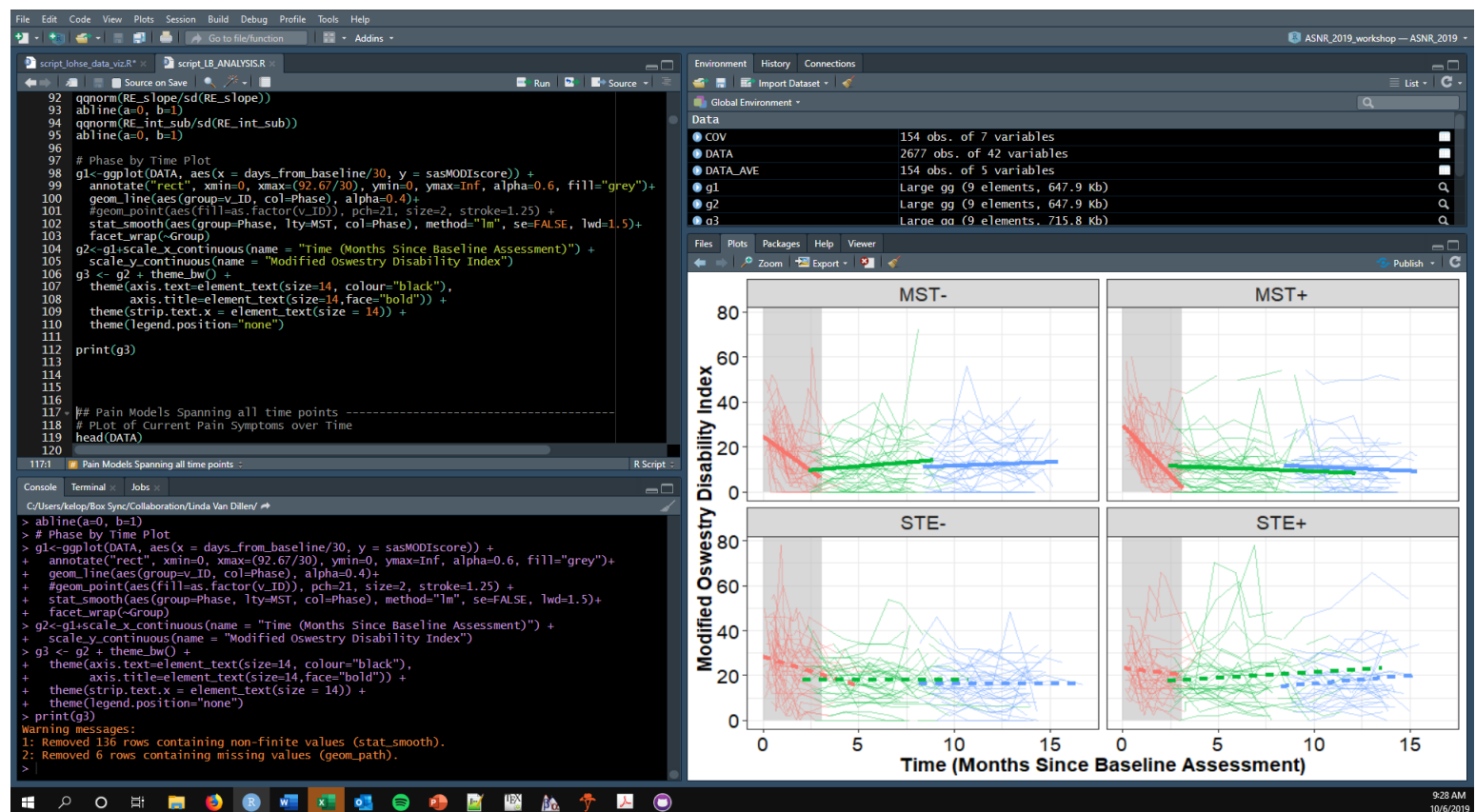
[Anscombe, 1974]

IMO, Good Visualizations Should...

1. **Put your data on the table.** Show “person-level” data and “group-level” statistics to paint the complete picture.
2. **Reduce unnecessary complexity.** The question motivating a visualization should be clear, as should the answer.
3. **Have correspondence to your analysis.** I can “see” your result without understanding the finer points of your analysis. The inferential statistics are just there to “back it up”.
4. **Accept uncertainty.** The data should speak for itself and visualizations should accurately reflect the data above all else.

[But see Healy, 2018; Tufte, 2001; Tukey, 1980; Wickham & Grolemund, 2017]

Reproducible, code based graphics.



- Ultimately, any way you create your visuals is fine as long as your visuals are accurate and informative.
- **But**, code-based approaches have a lot of advantages in terms of efficiency and reproducibility.

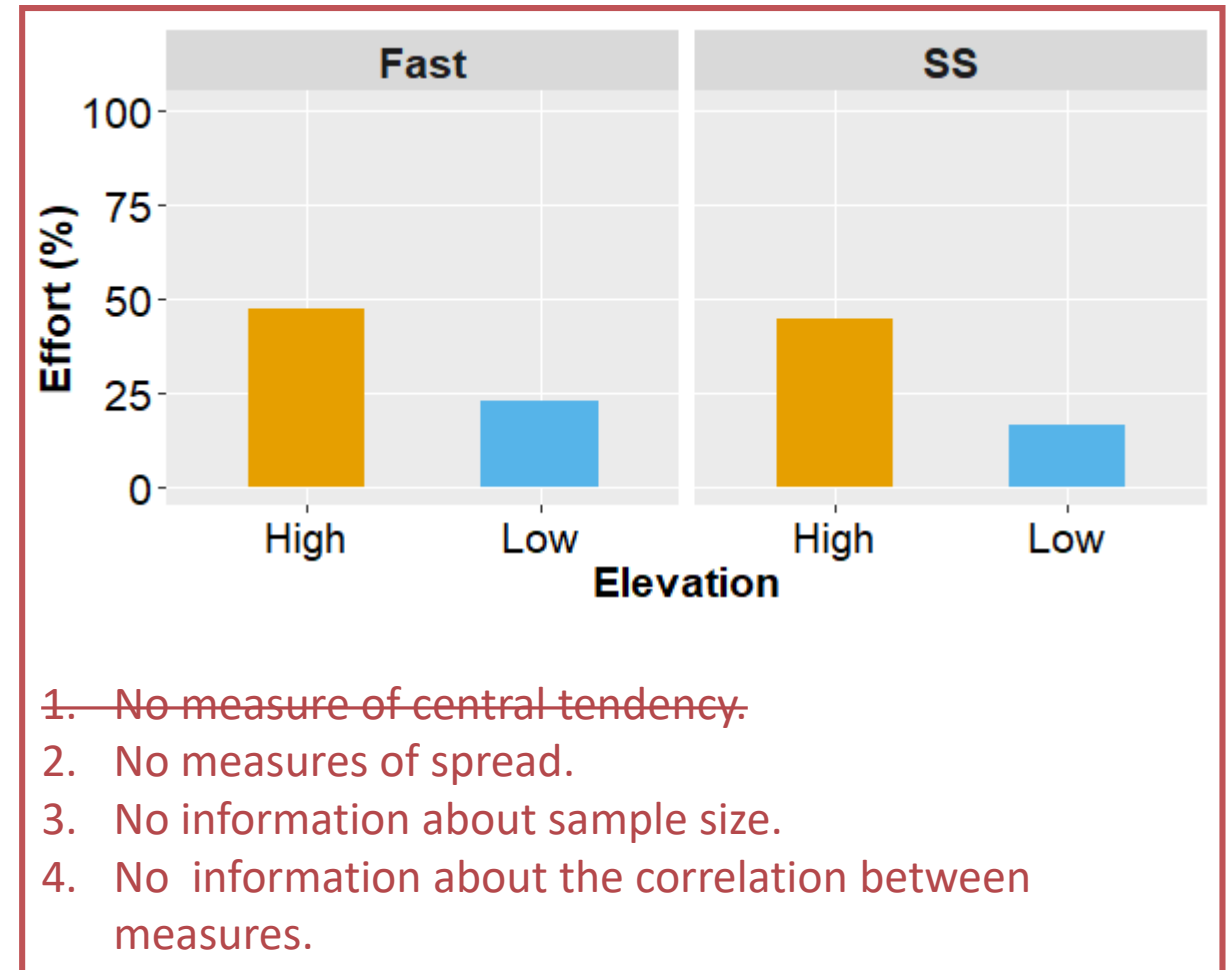
[I create most of my graphics in 'ggplot2' using R. Any post-processing I do in the Gnu Image Manipulation Program.]

Visualizing Discrete Data

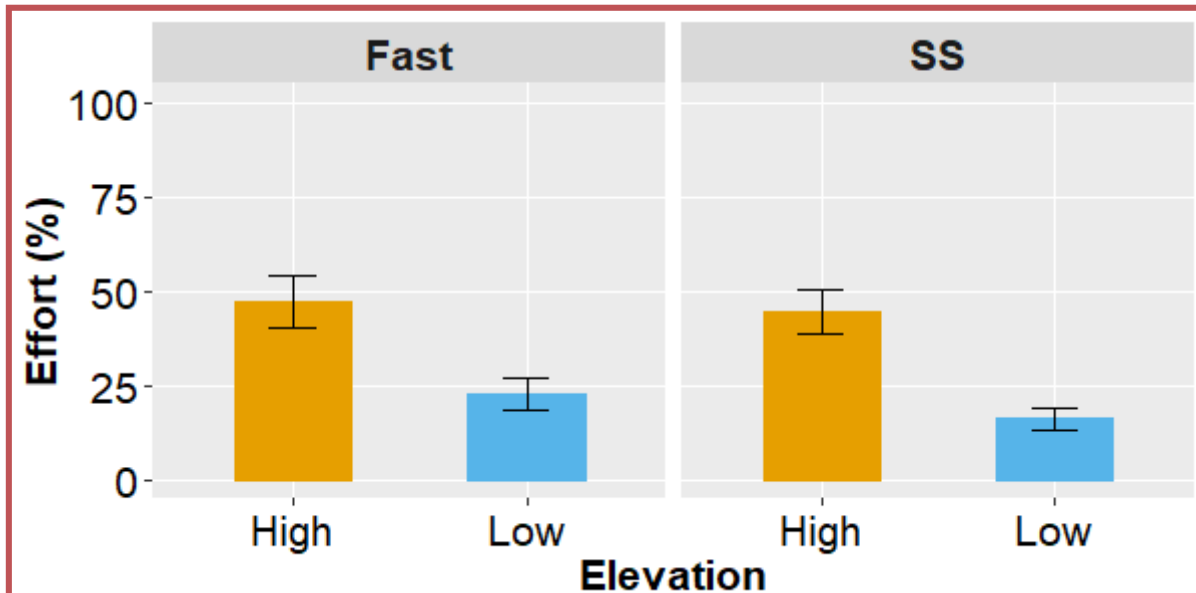


Consider a 2 x 2 factorial design.

- Participants walked at fast or selected speeds at virtual high or low heights.
- Among other things, we collected psychological perceptions of effort across the different trials.



Consider a 2 x 2 factorial design.

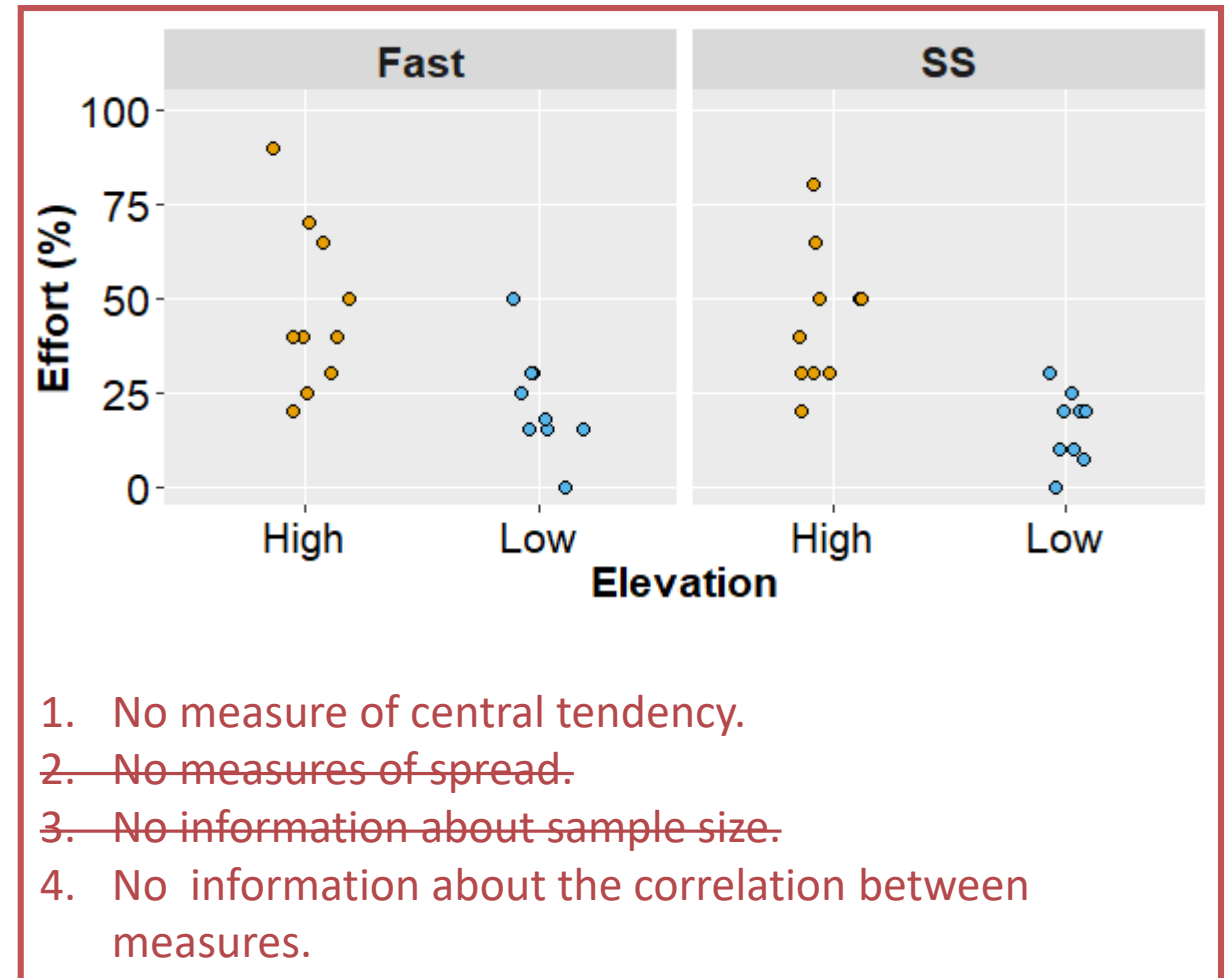


- ~~1. No measure of central tendency.~~
- ~~2. No measures of spread.~~
3. No information about sample size.
4. No information about the correlation between measures.

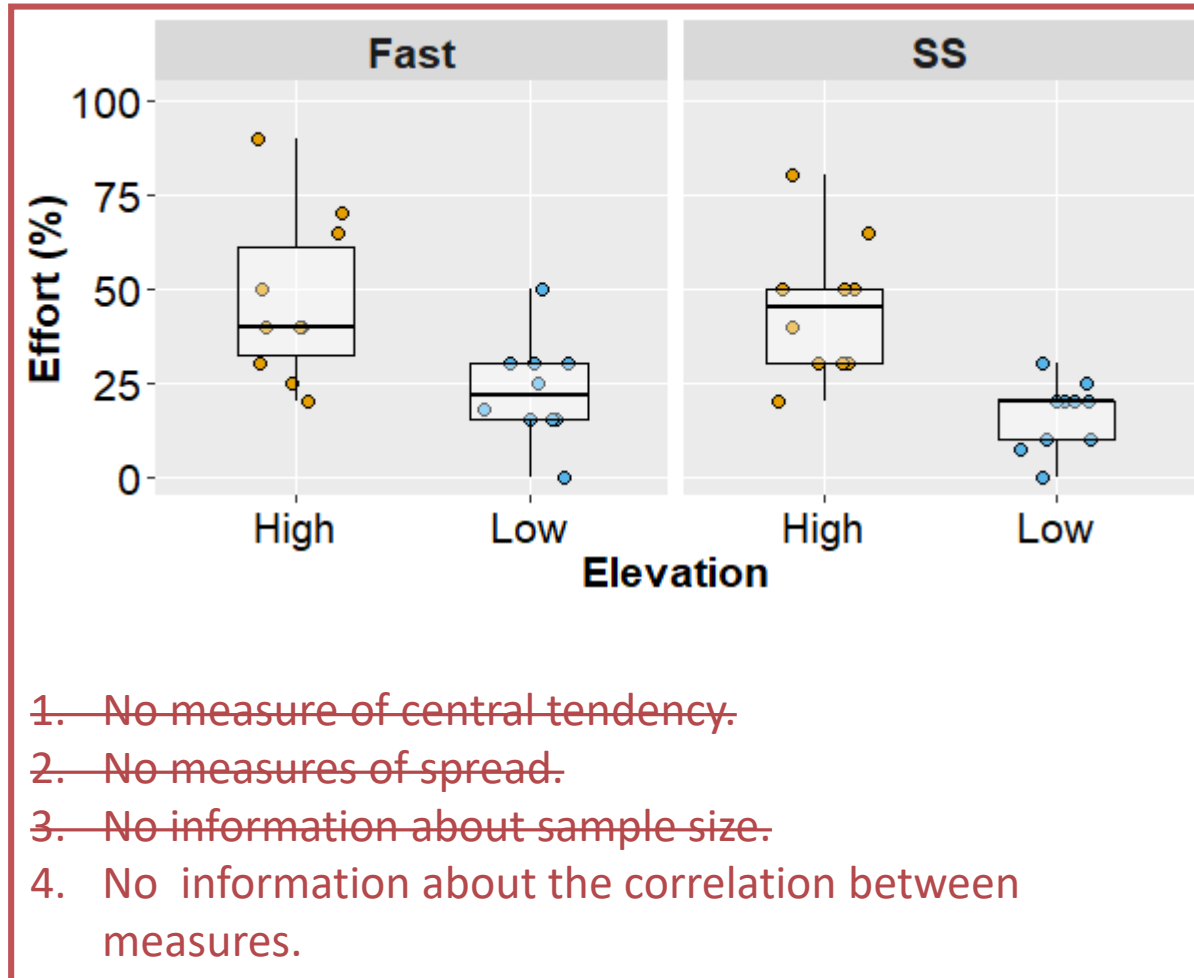
- Adding standard errors is arguably better **but...**
 - These are between subjects standard errors, and our manipulation occurred within subjects. [Loftus & Masson, 1994; Morey, 2008]
- The standard error confounds standard deviation with sample size, $se = s/\sqrt{n}$.

Consider a 2 x 2 factorial design.

- What if we just plot all of the data?
- To paraphrase Karl Pearson, we have now put our “data on the table”, **but** something has also been lost. [Stigler, 2002]
 - Measures of central tendency are critical to our statistical inference.
 - We have gained a rich description of our sample, but lost the correspondence to our analysis.



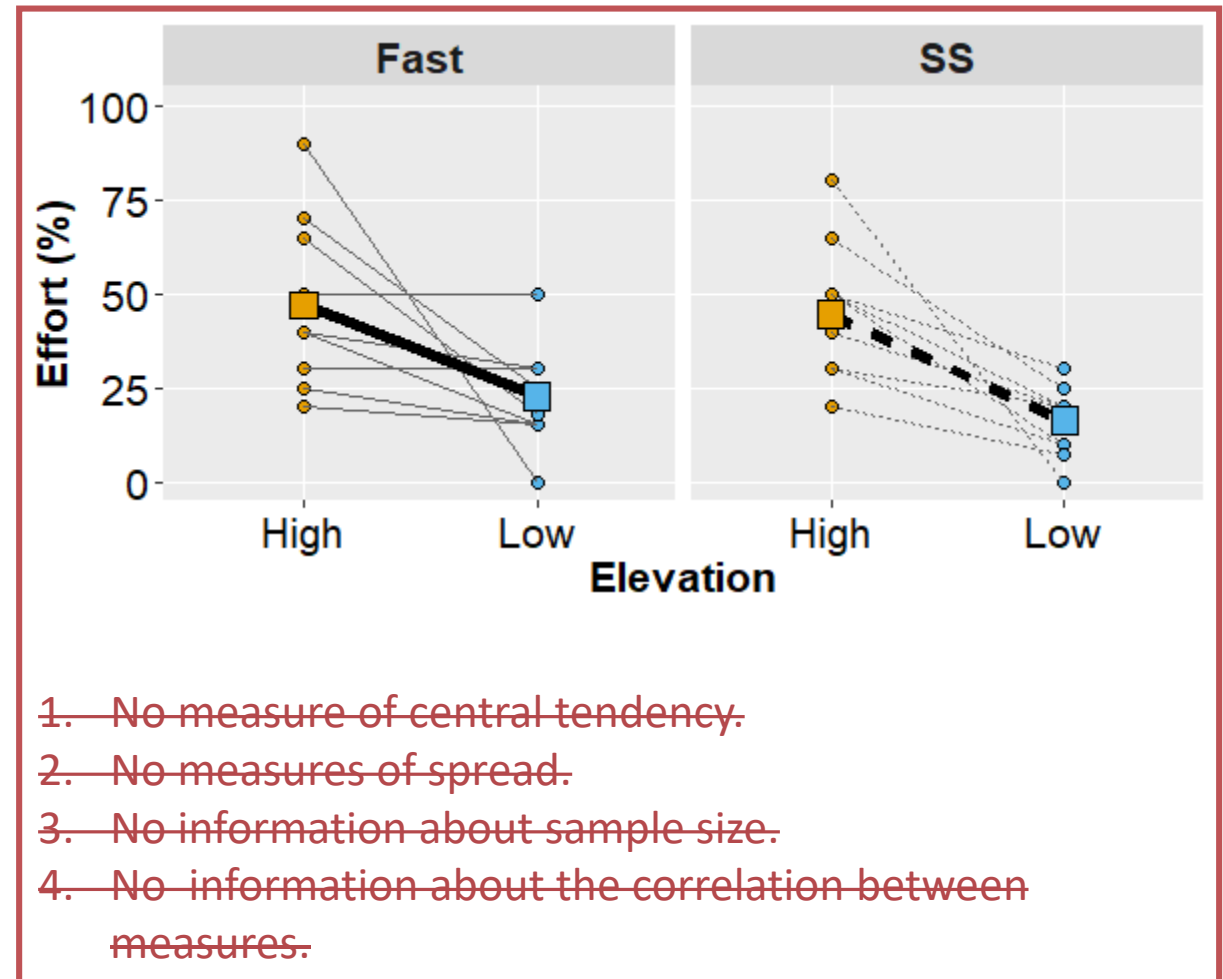
Consider a 2 x 2 factorial design.



- Now this is good! By playing with overlay and transparency, **group-level** statistics are emphasized (for inference).
- But all of the **participant-level** data are also visible (for description/assumptions).
 - One issue is that boxplots show medians, but most of our inferential statistics are based on means.
 - This isn't bad, but potentially lacks correspondence between visualization and analysis.
- In a within-subject design, we might want to know which points belong to whom.

Consider a 2 x 2 factorial design.

- We can overlay the means for each condition on top of the data for each condition.
- By connecting the dots, we can also provide information about the correlation between conditions.

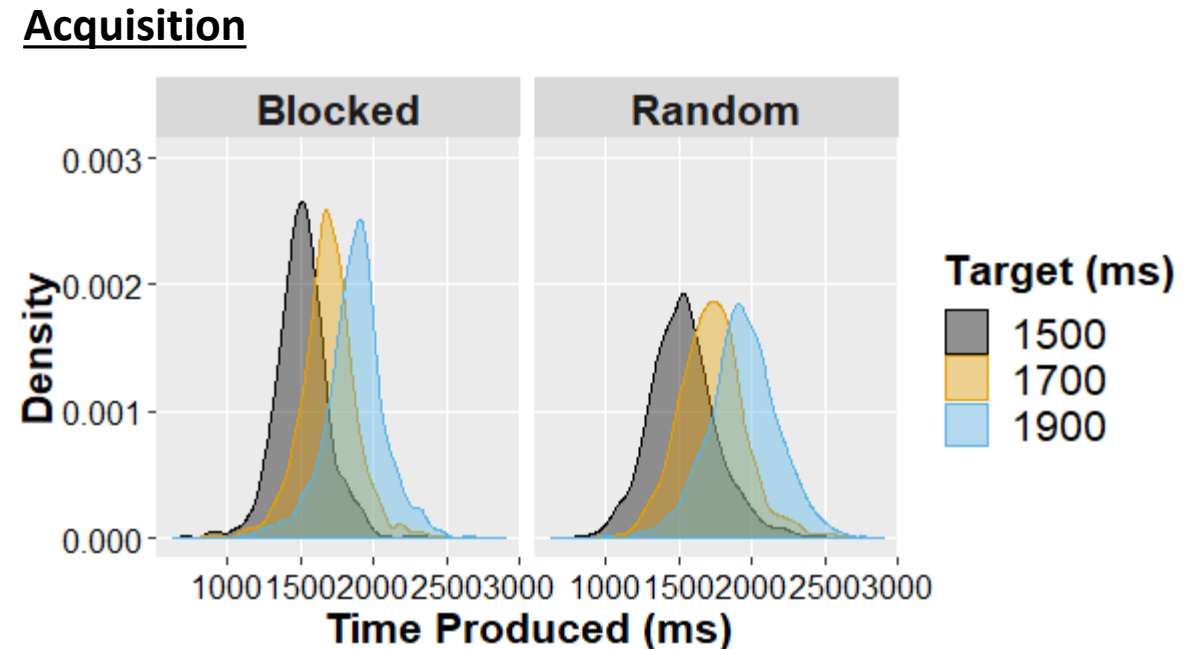


Visualizing Continuous Data



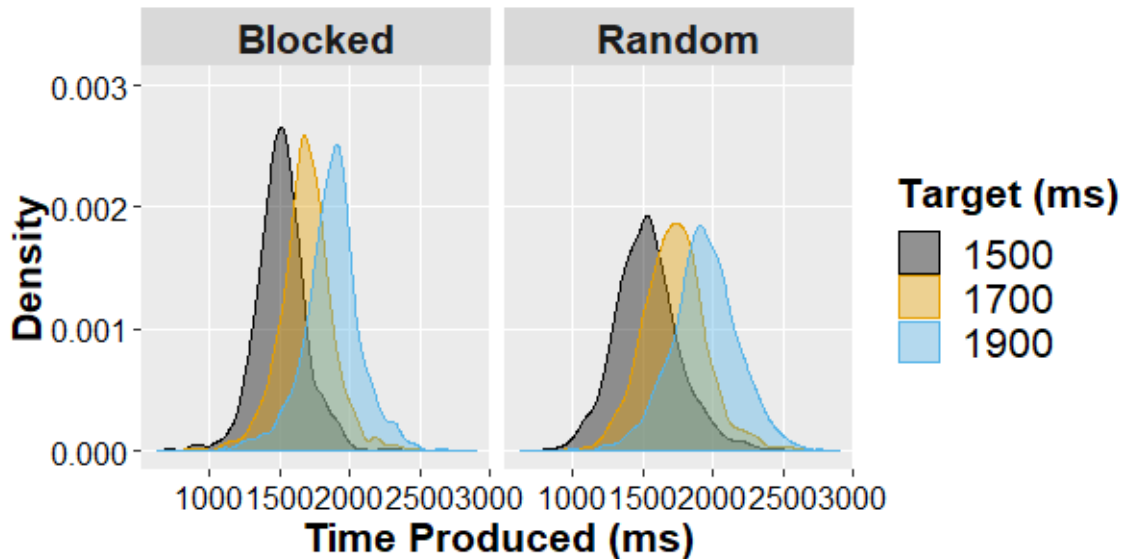
A Two Group Longitudinal Study

- In a variable versus blocked practice experiment, participants learned to estimate different intervals of time in either a **blocked** order or a **random** order.
 - 1500 ms
 - 1700 ms
 - 1900 ms
- Focusing on response distributions to study '**confusability**'.

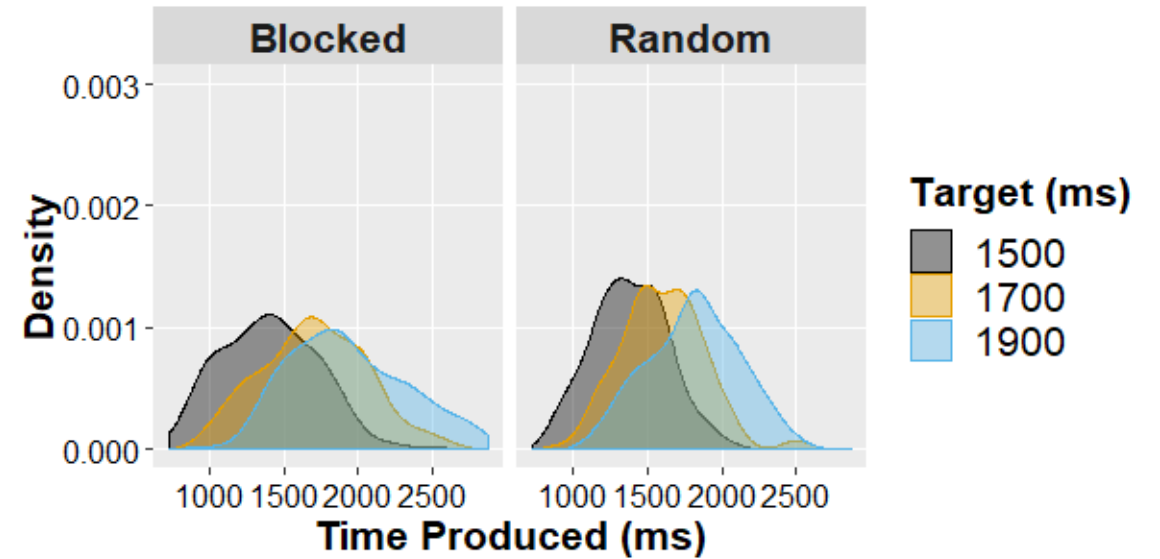


A Two Group Longitudinal Study

Acquisition



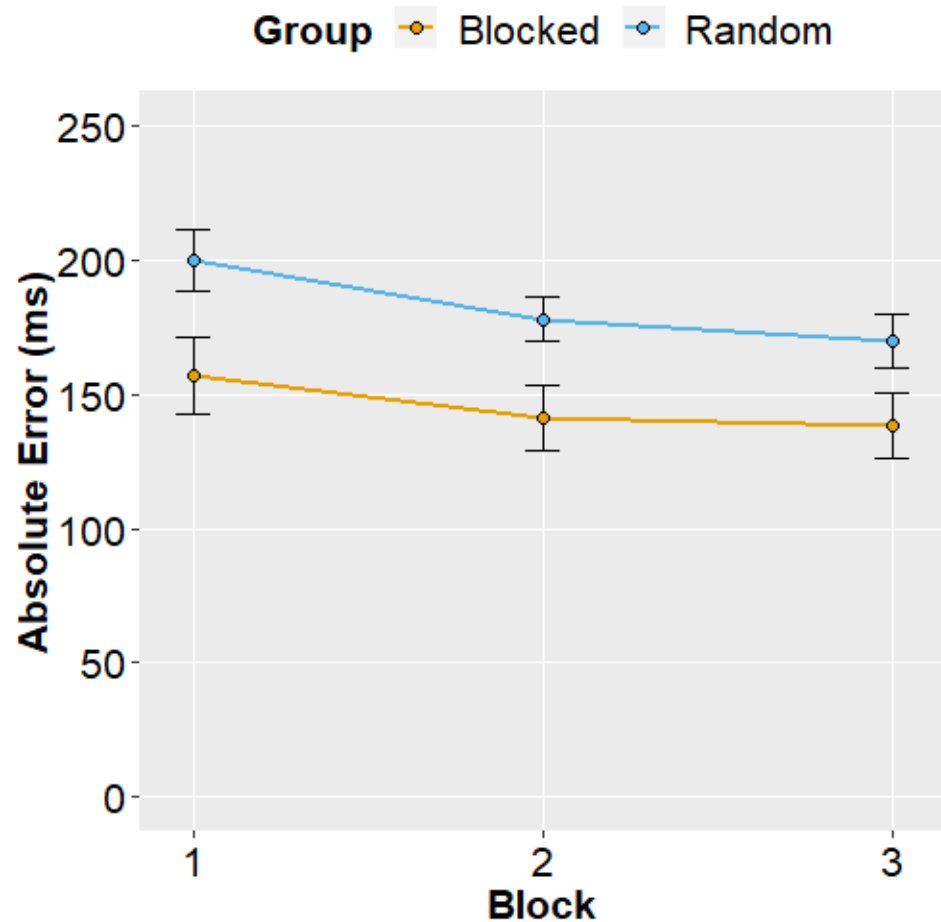
Delayed Retention Test



[Fall Out, InterPlay Ent.]

It's a slightly different way of looking at it, but we replicate the traditional contextual interference effect.

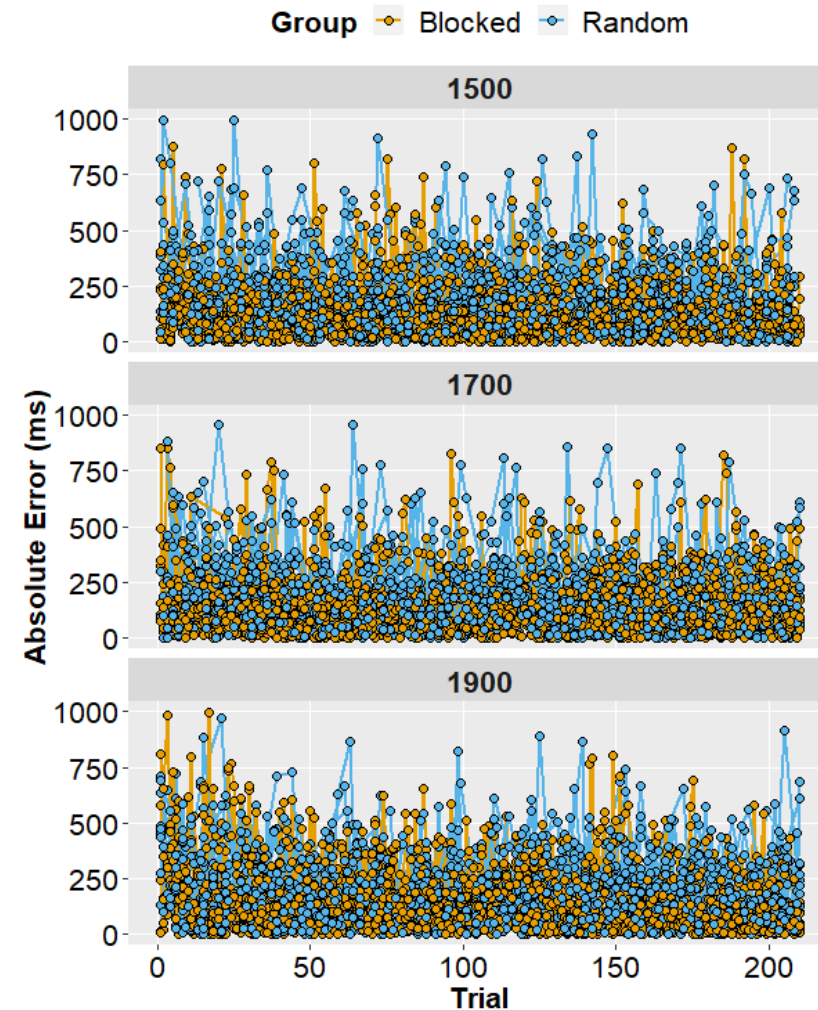
A Two Group Longitudinal Study



- But learning is a continuous process that happens over time.
- In a more “classic” plot, we might average across trials and targets to look at average error in each block of practice.

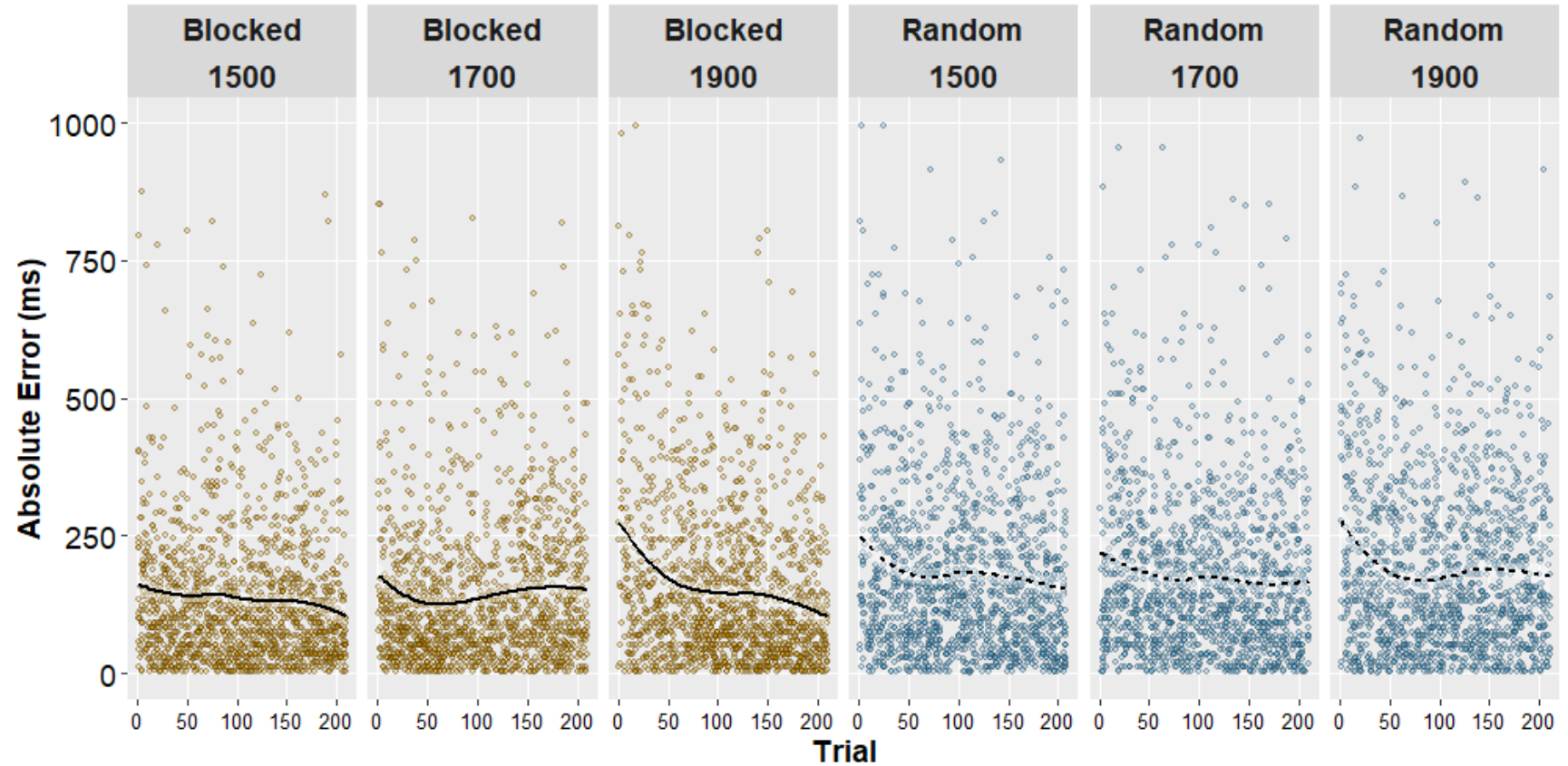
A Two Group Longitudinal Study

- What if I want to see all of the data?
- It's too much!
- We have so many acquisition trials that it makes identifying performance curves almost impossible.



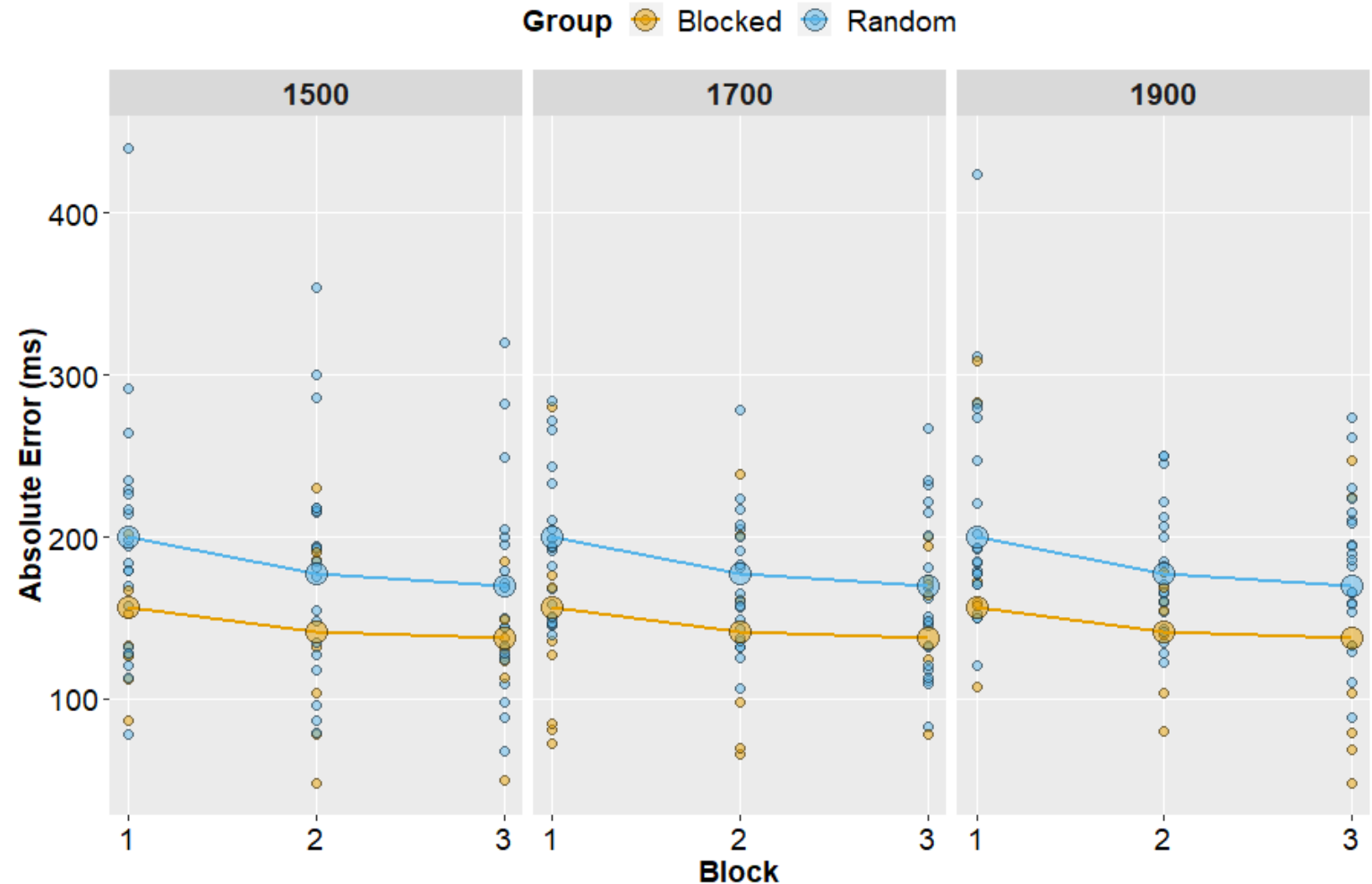
A Two Group Longitudinal Study

- However, by playing with aesthetic features such as spacing, transparency, and line type, we can make the overall pattern much more interpretable.



A Two Group Longitudinal Study

- With a little bit of aggregating, we might be able to find a happier “middle ground”.



Thank You!



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