Beyond Weber's Law

A second look at ranking visualizations of correlation

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University of Washington

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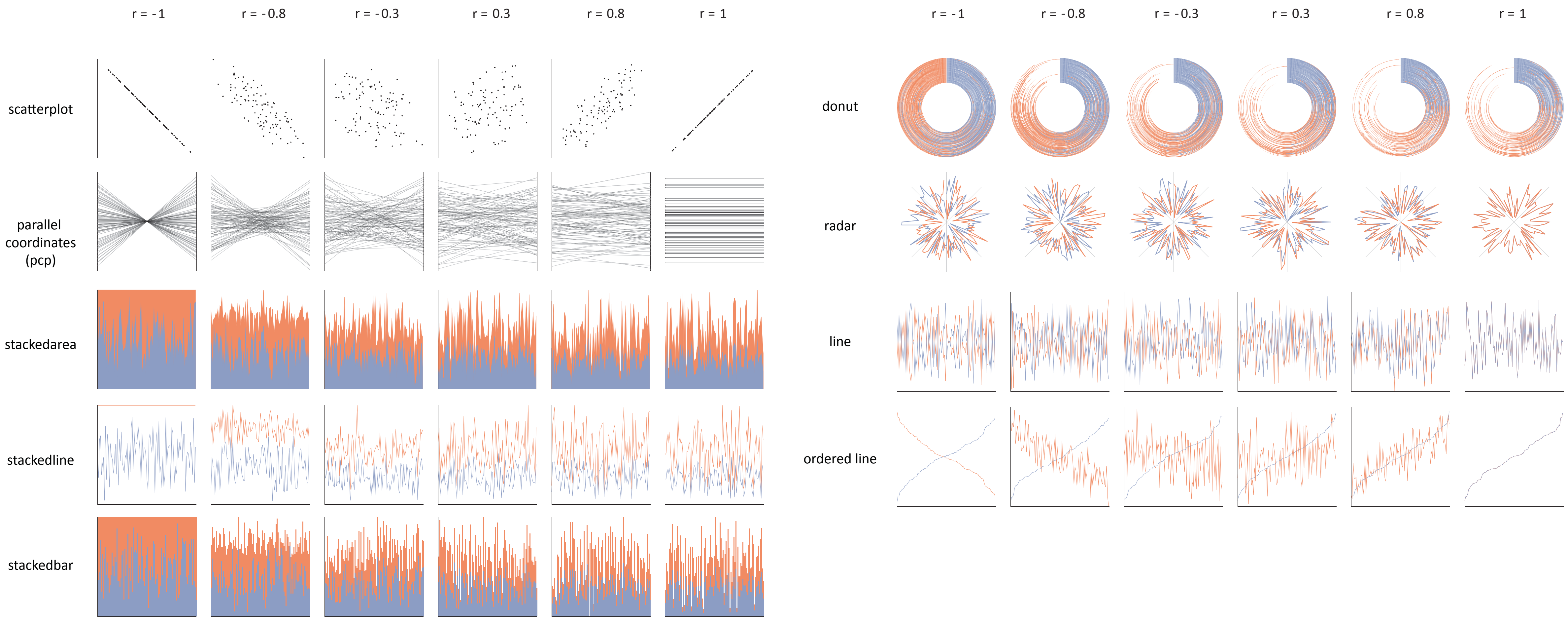
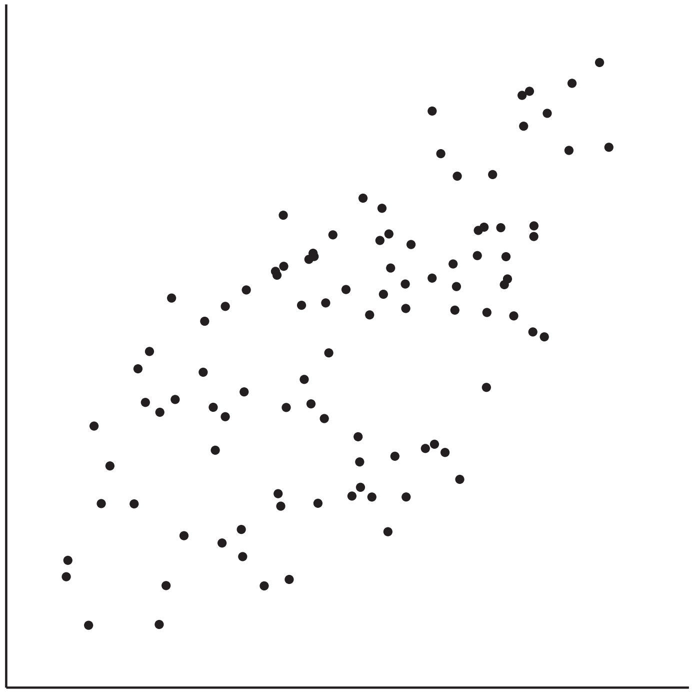
We re-analyzed Harrison *et al.*
from InfoVis 2014



[adapted from Fig. 3, Harrison *et al.*, InfoVis 2014]

Estimating precision: just-noticeable differences



r = .65

[adapted from Fig. 1, Harrison *et al.*, InfoVis 2014]

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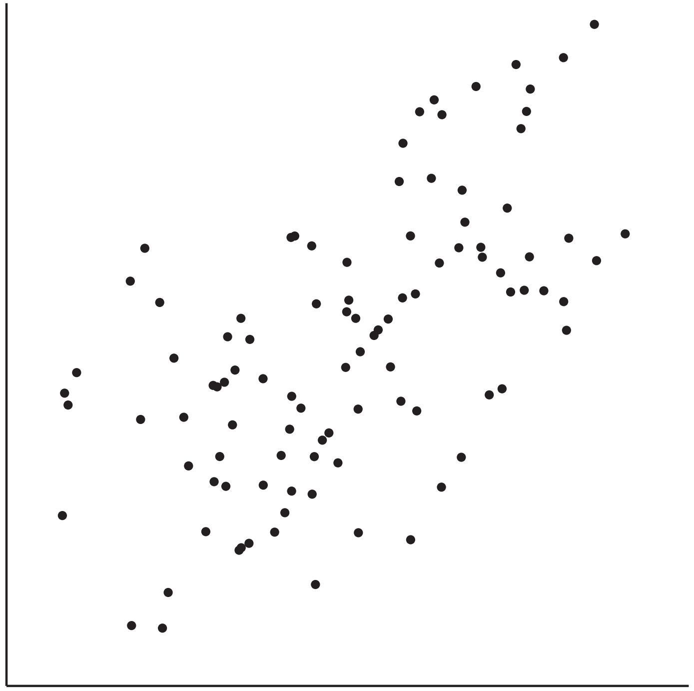

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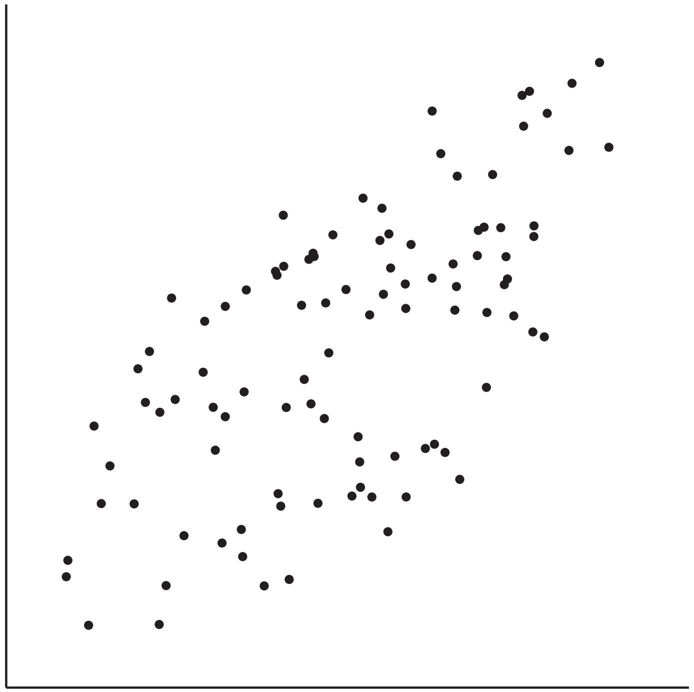

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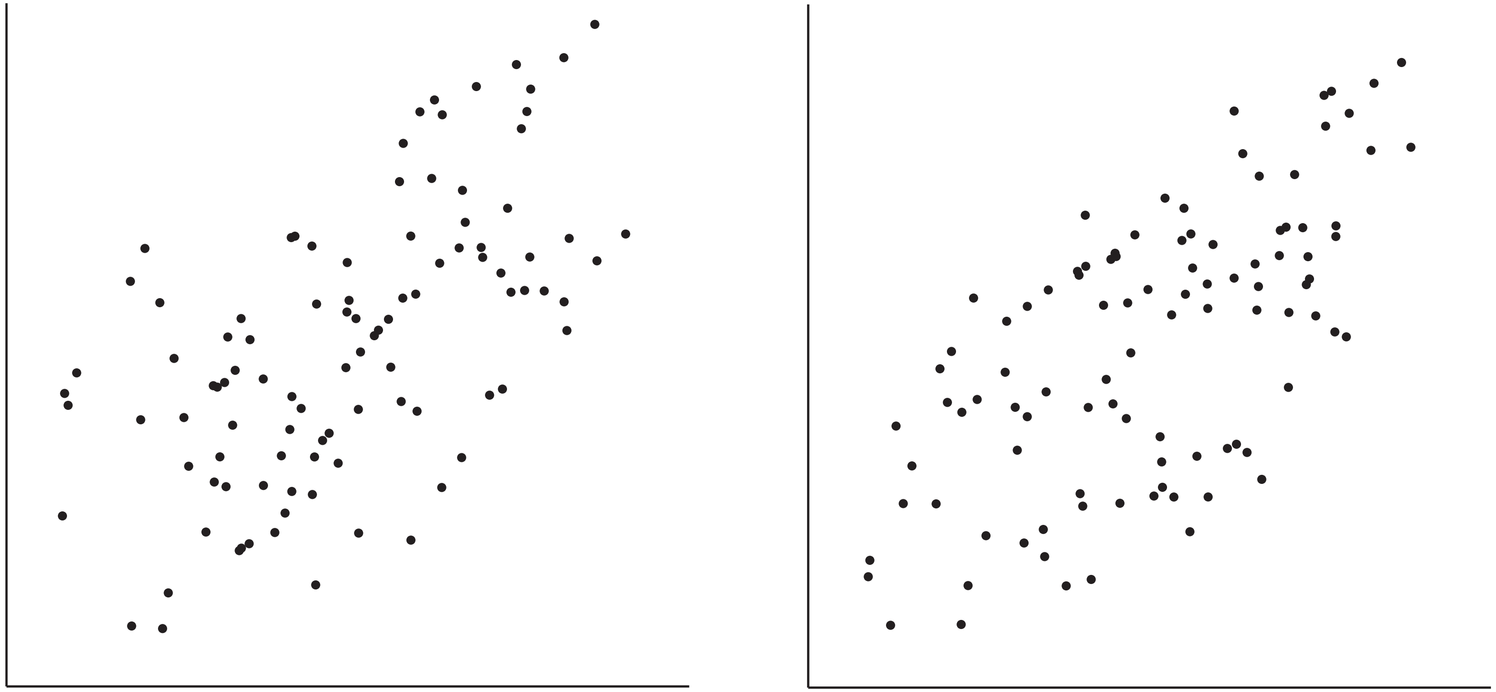

r = .6 r = .65

JND from below

[adapted from Fig. 1, Harrison *et al.*, InfoVis 2014]

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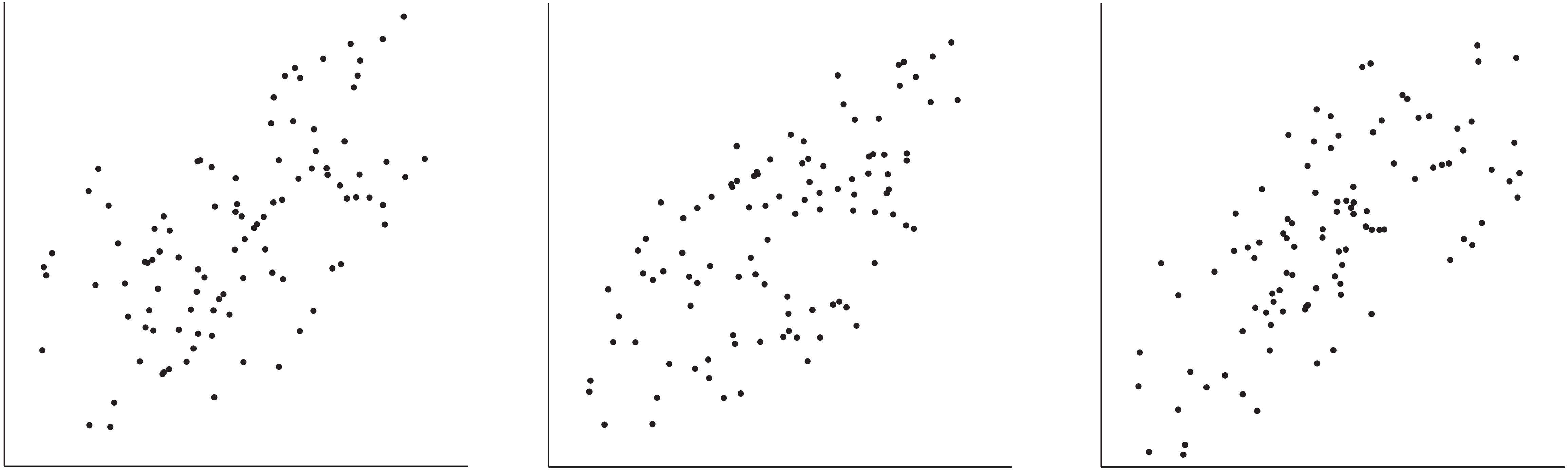
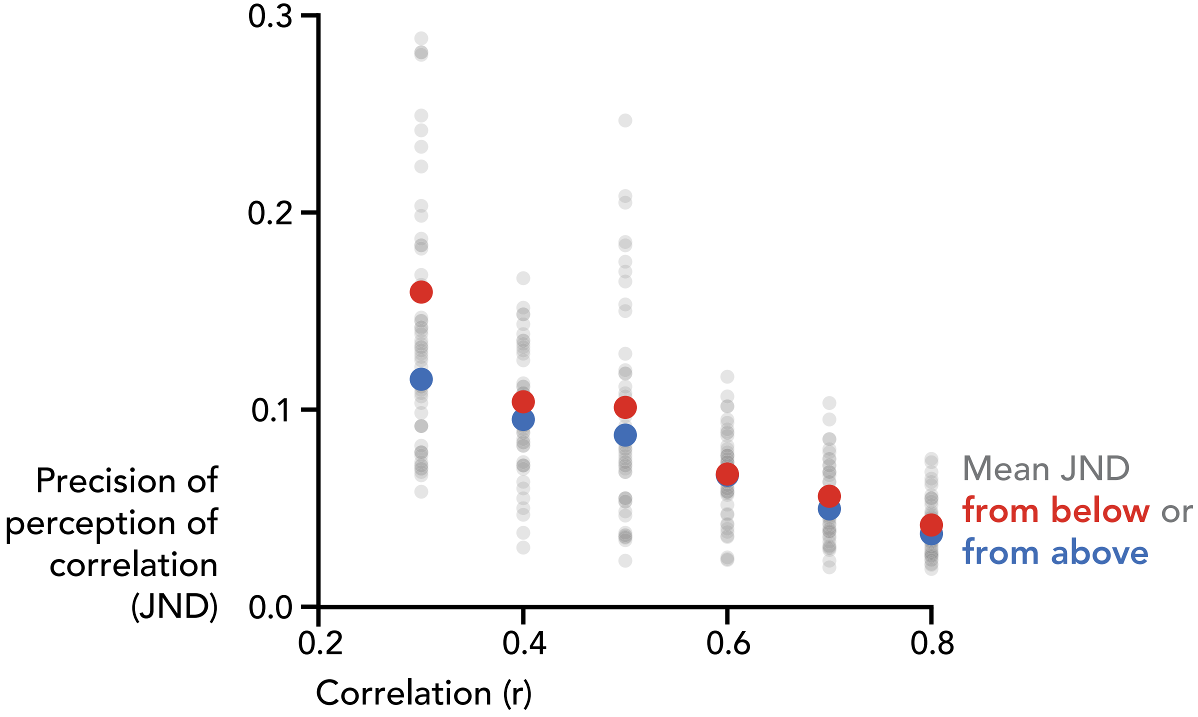


r = .6 r = .65 r = .7

JND from below JND from above

[adapted from Fig. 1, Harrison *et al.*, InfoVis 2014]

A **Weber** model for scatterplot-positive as in Harrison *et al.* [InfoVis 2014]



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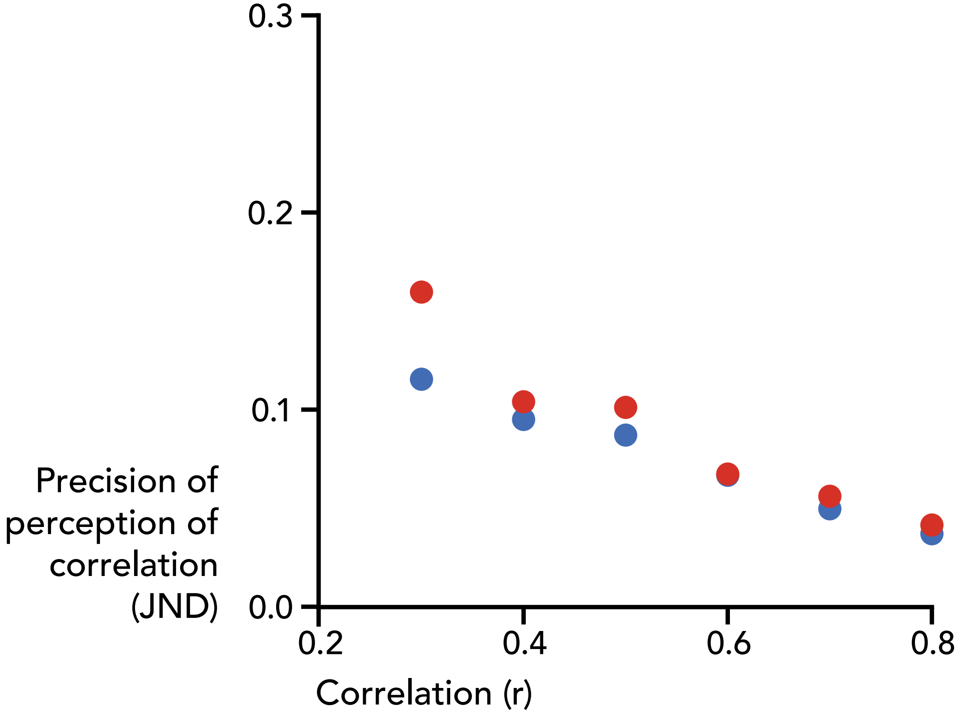

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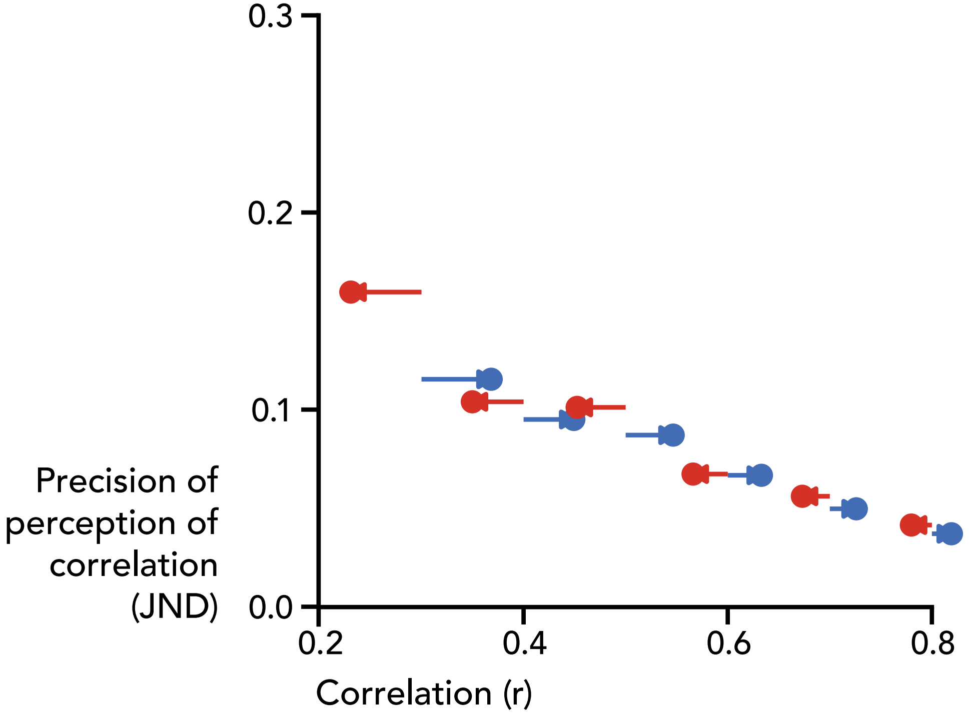

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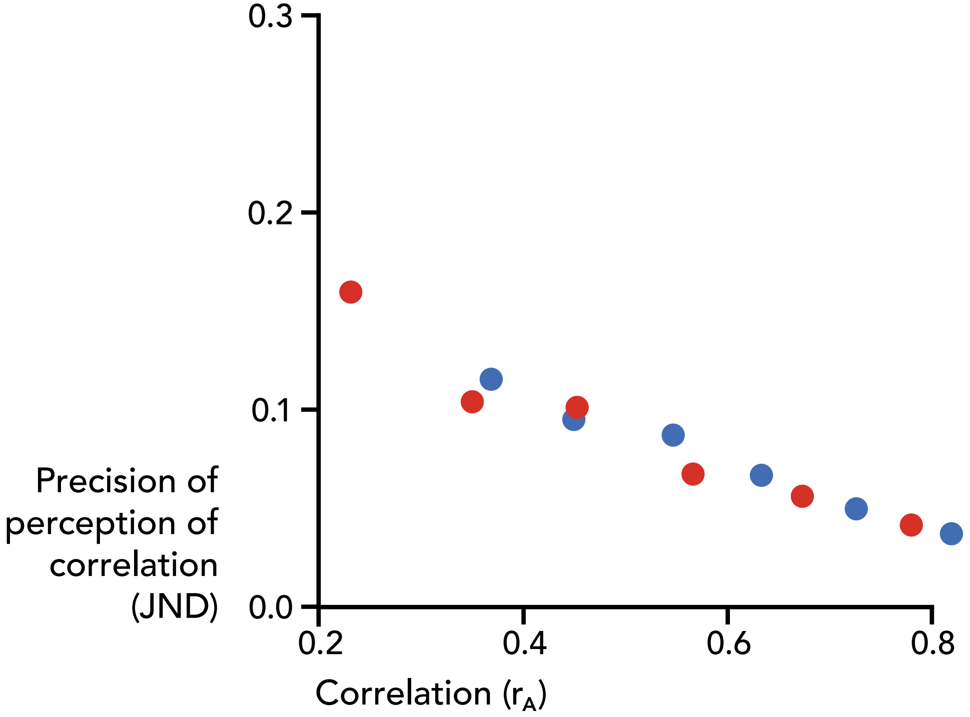

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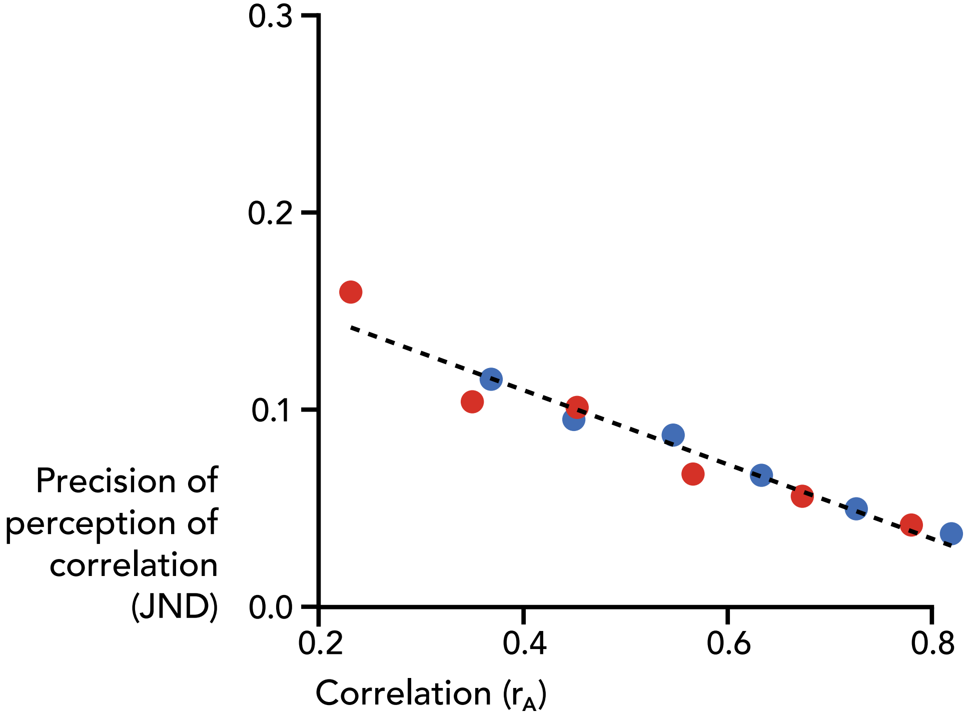

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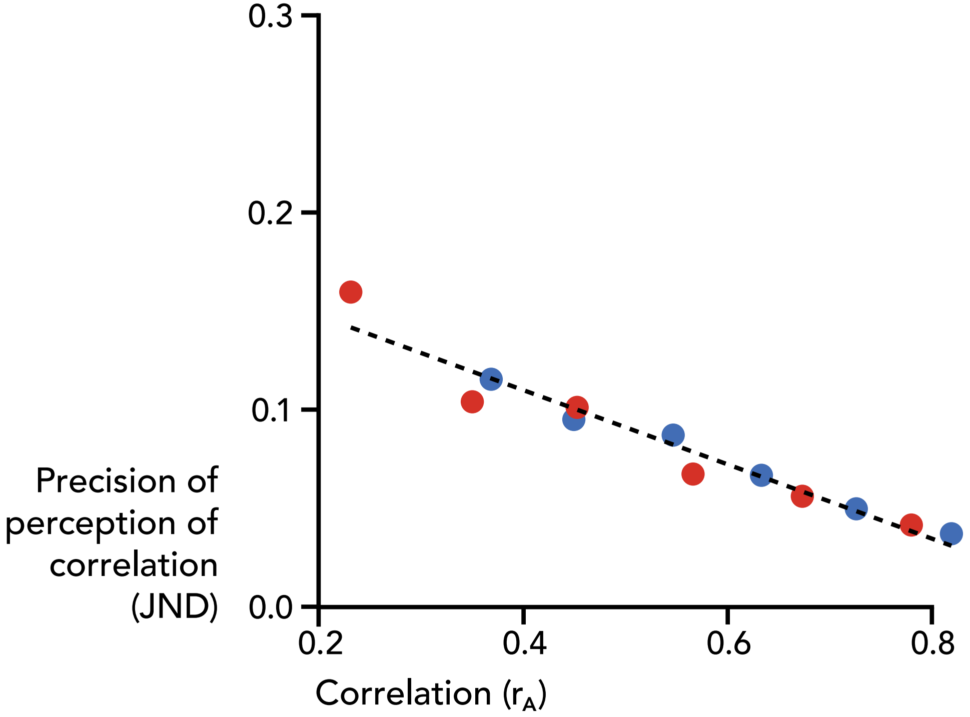
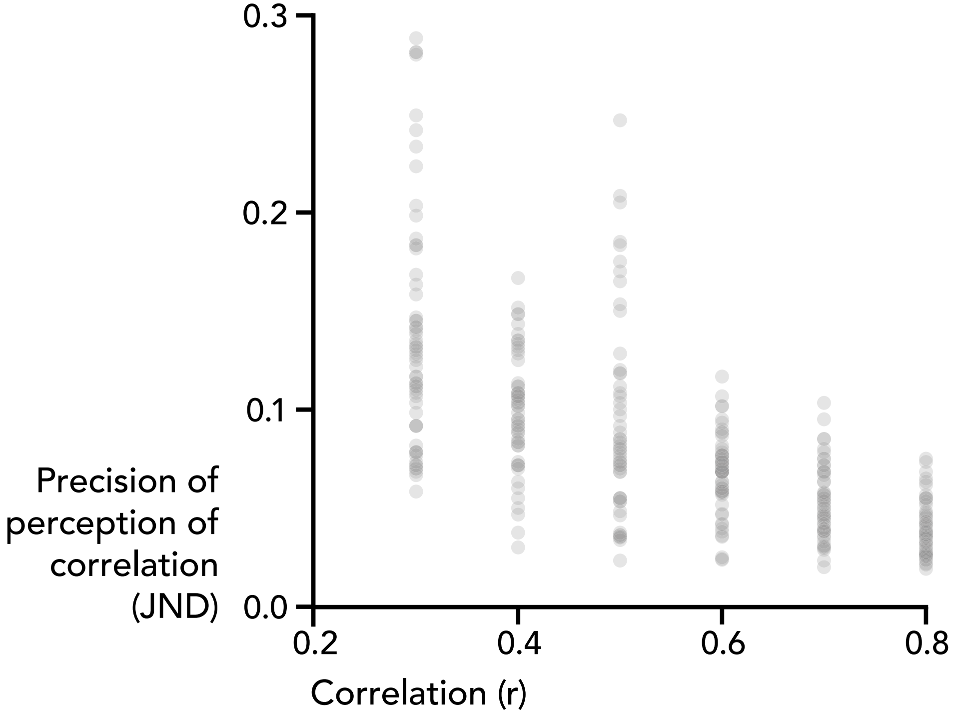


A log-linear (**non-Weber**) model as in this paper



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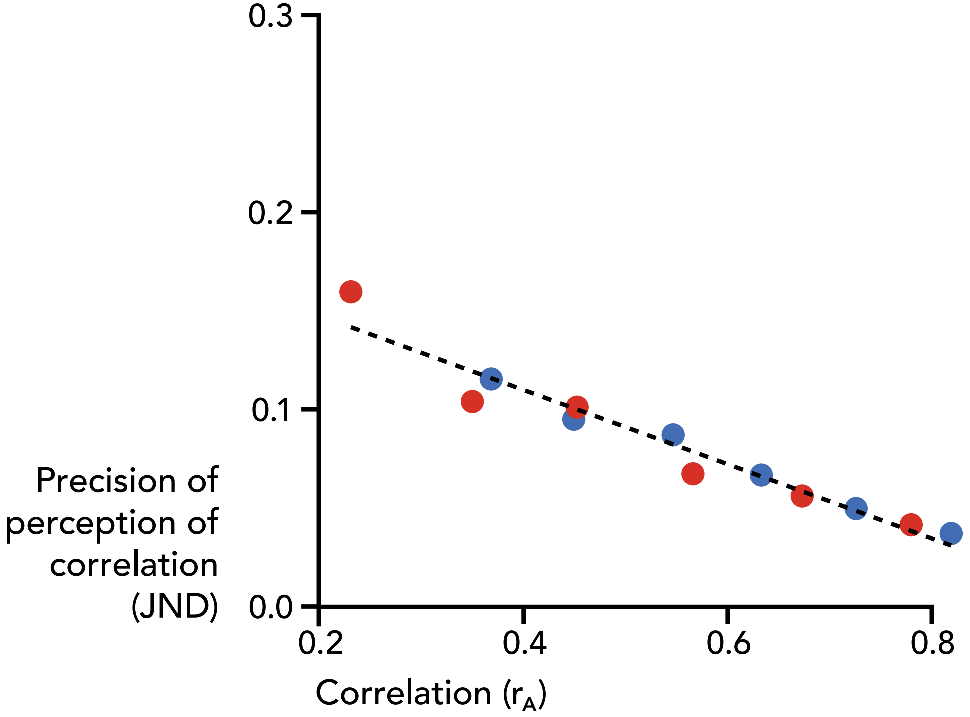

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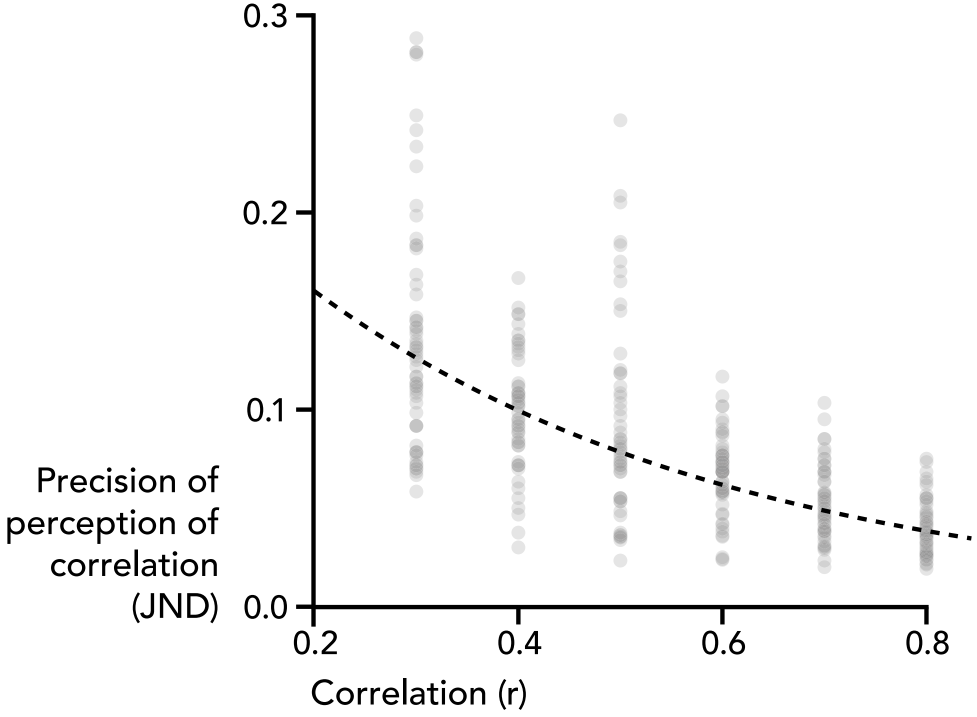

The high level bit

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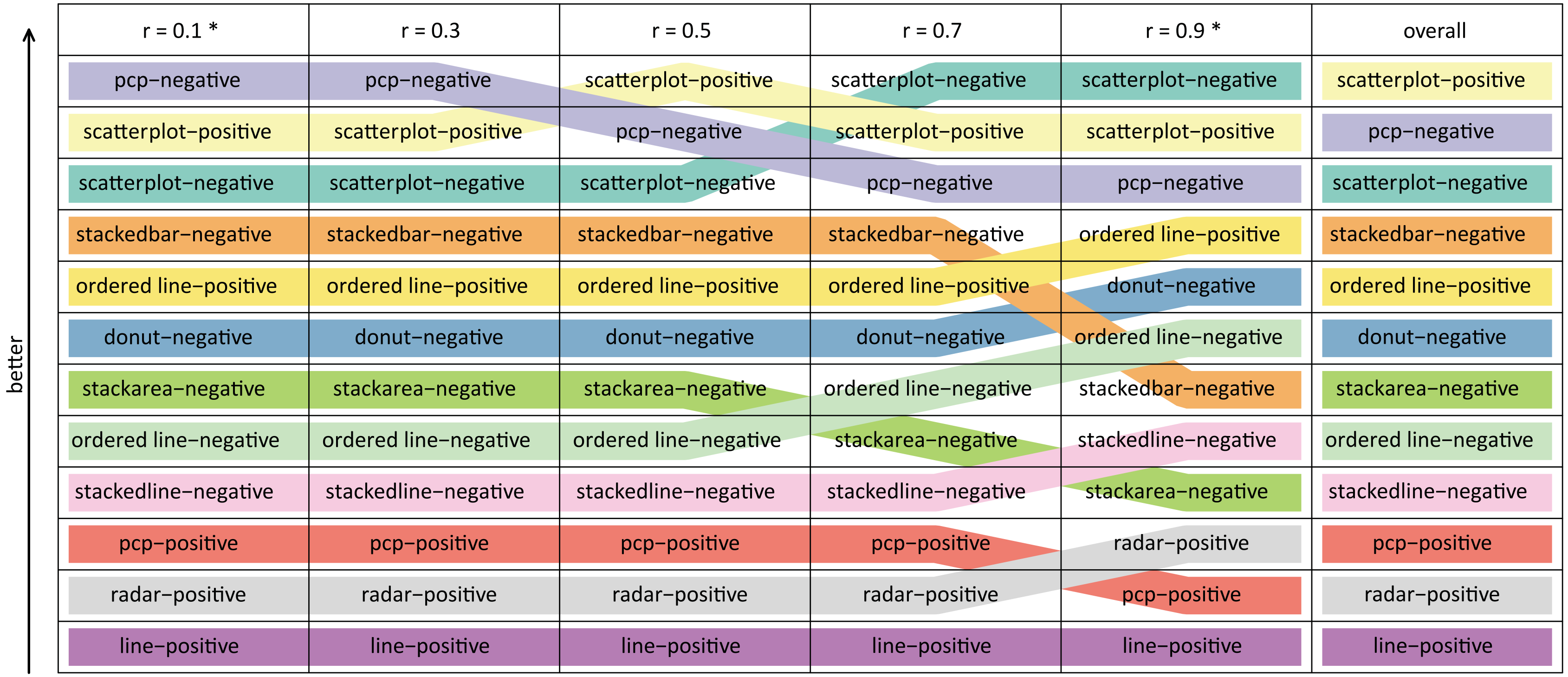
Harrison et al.'s recommendations:



[Fig. 7, Harrison *et al.*, InfoVis 2014]

The high level bit

Our recommendation:

After considering model error, practical effect sizes, and variance between individuals,

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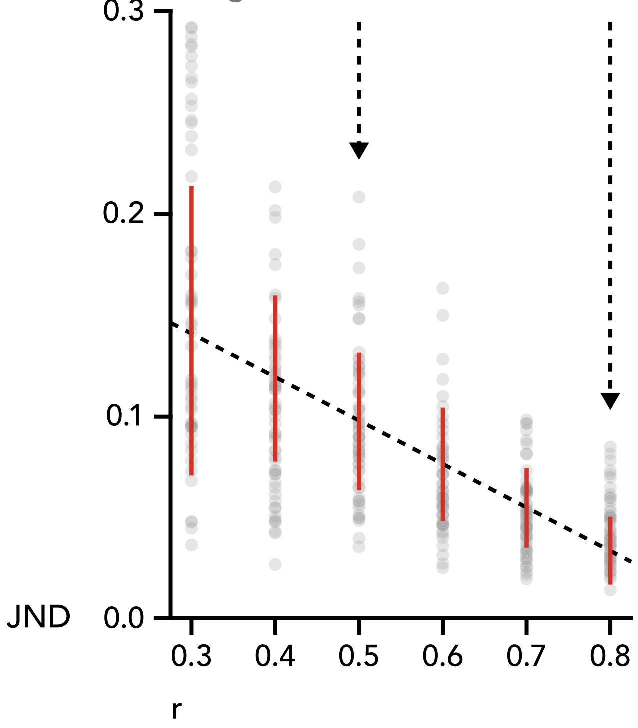
After considering model error, practical effect sizes, and variance between individuals,

Just use scatterplots.

How did we get there?

Fitting the linear model to individual observations

1. This example fit for scatterplot–negative shows **non-constant variance**: When r is large, the **scale** of the residuals shrinks.



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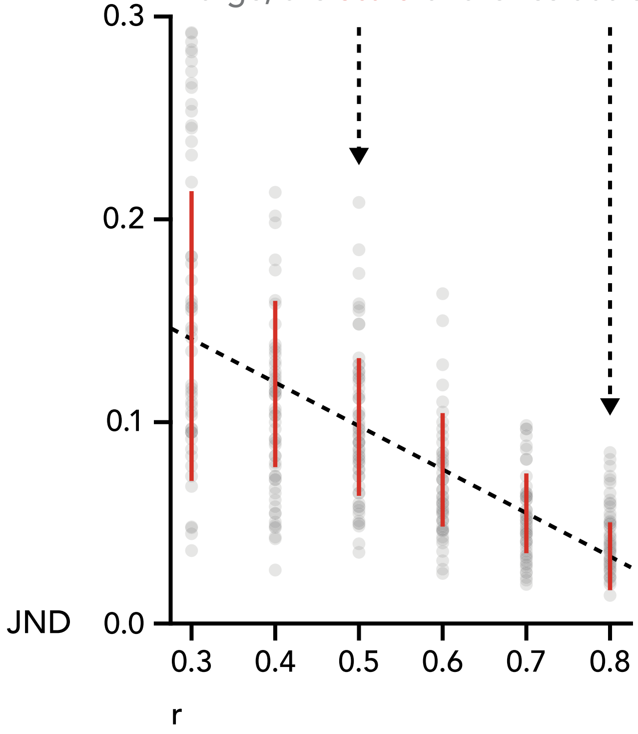
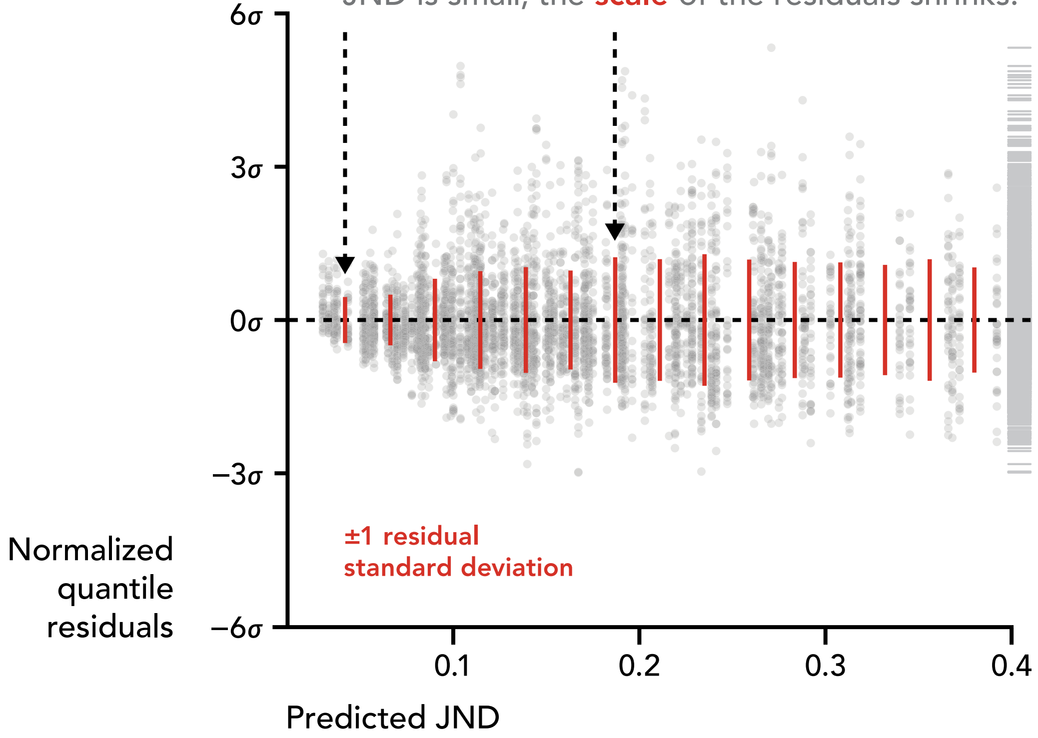


2. The combined fit for all visualizations also shows **non-constant variance**: When the predicted JND is small, the **scale** of the residuals shrinks.



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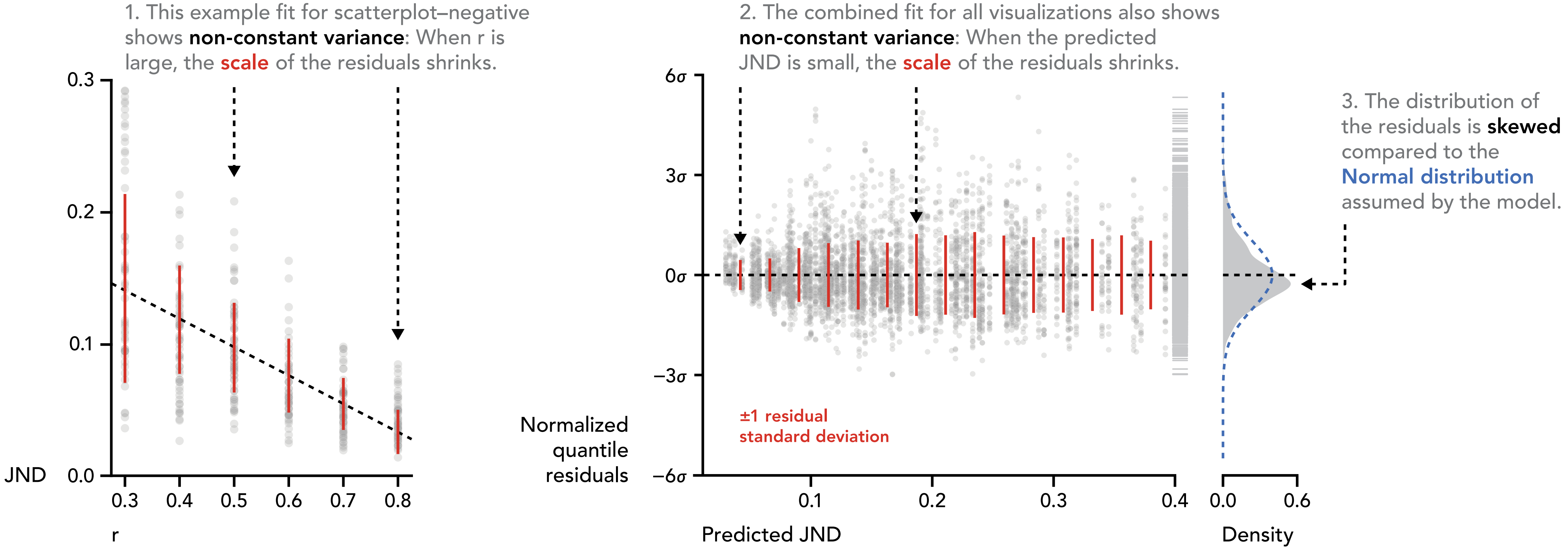
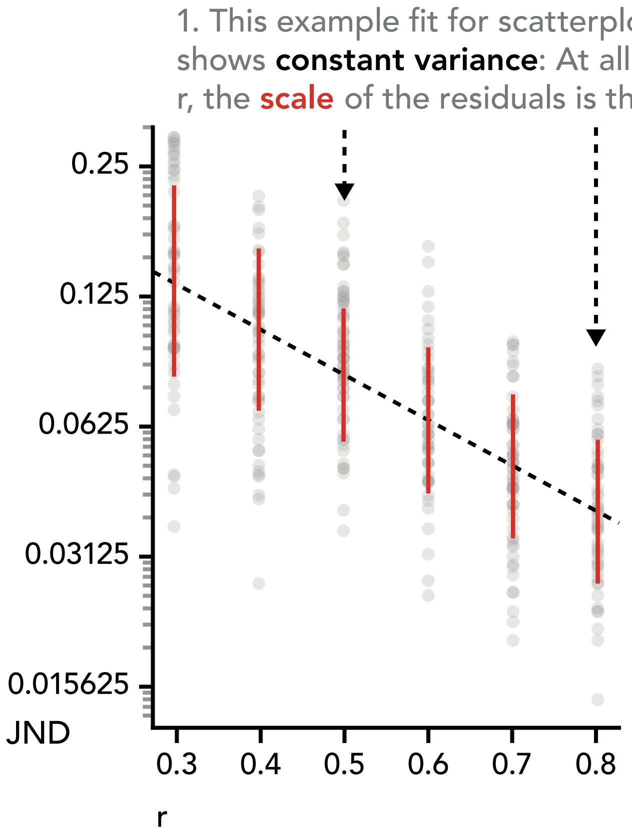
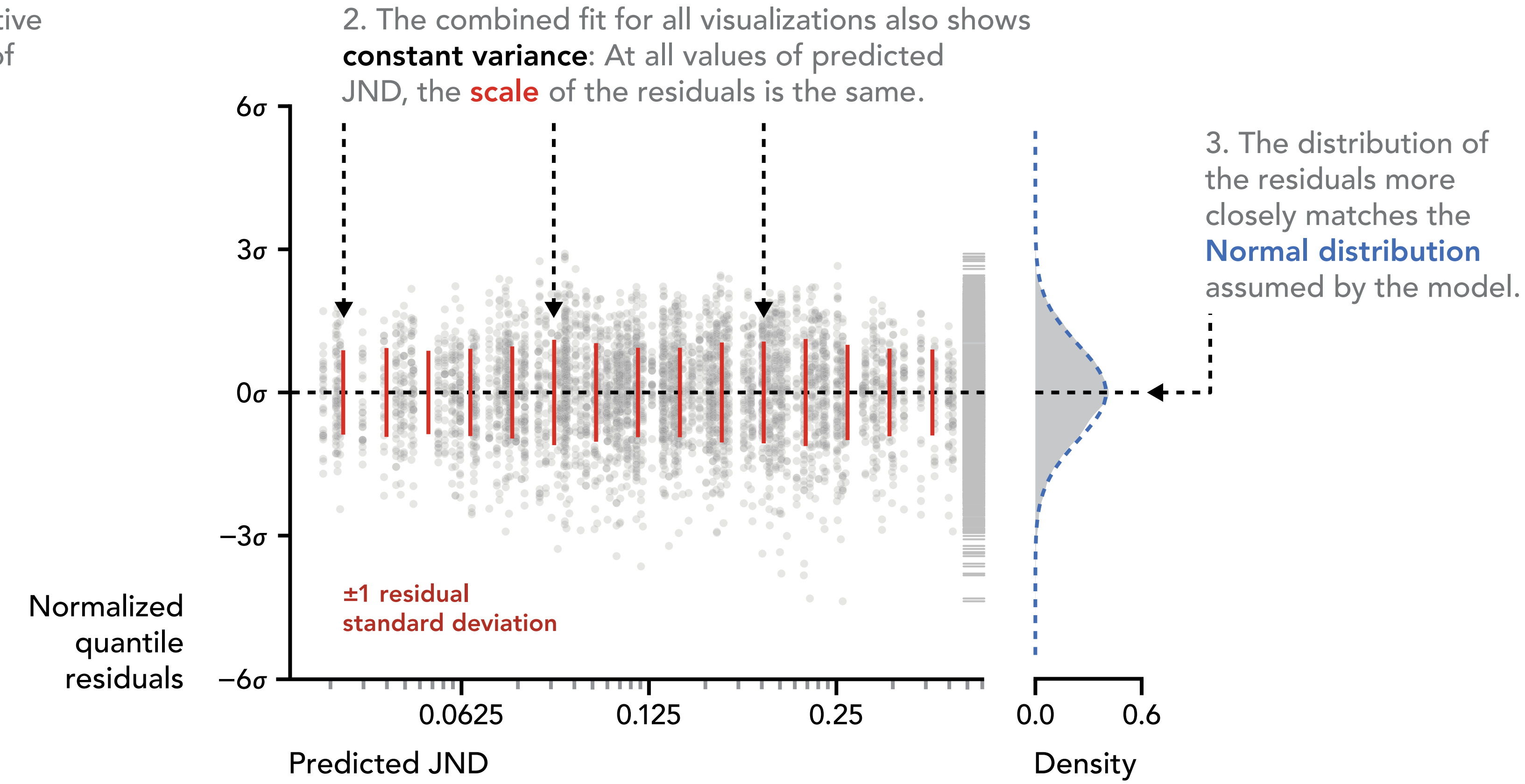


Alternative model: log-transformed responses





Accounting for outliers using censoring

Harrison et al. dropped several observations (and a few conditions) as outliers.

We included these all observations and conditions by employing censored regression.

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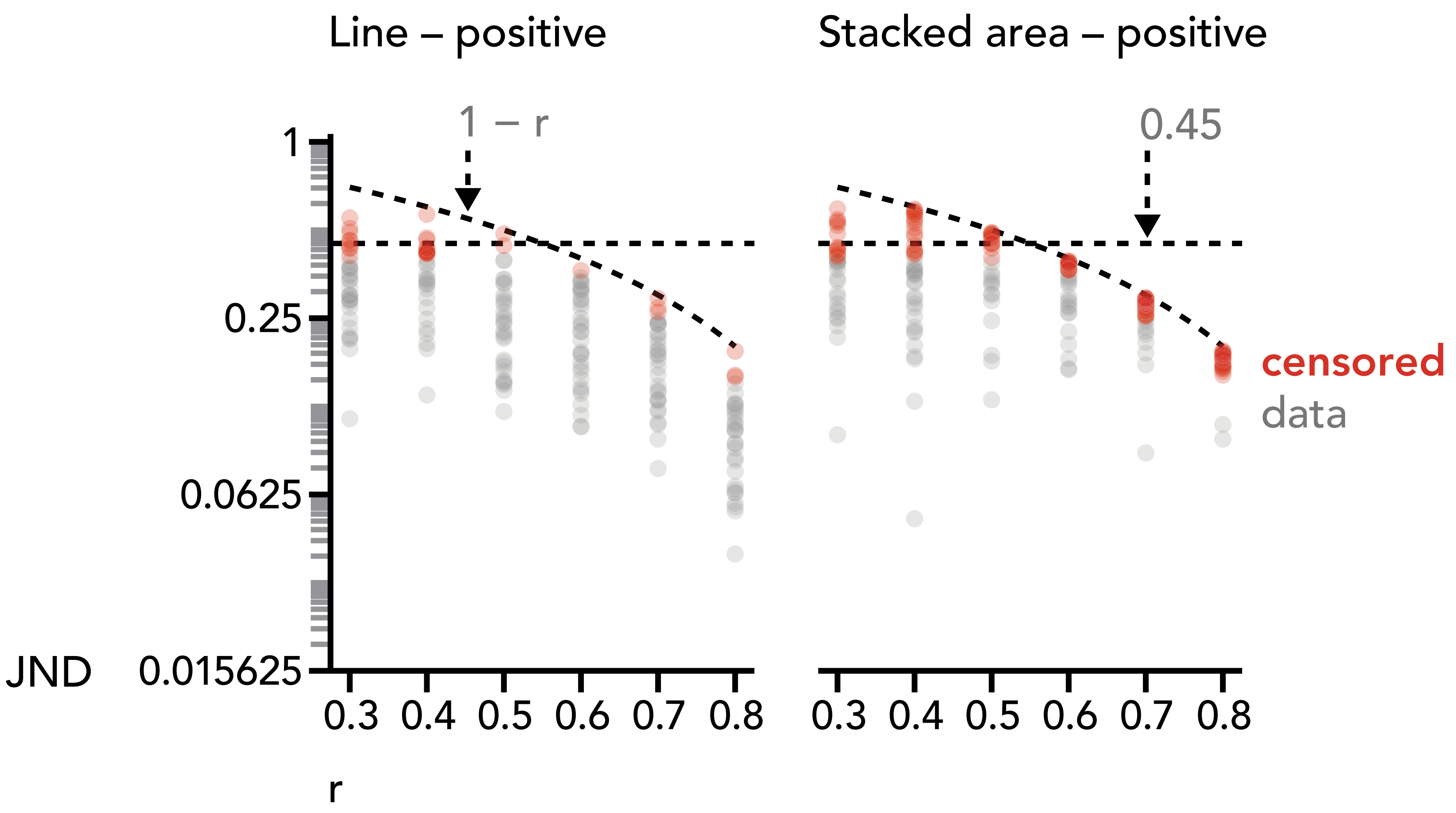

Bayesian mixed-effects modelling

We used a Bayesian model, incorporating skeptical priors based on Rensink and Baldridge [2010].

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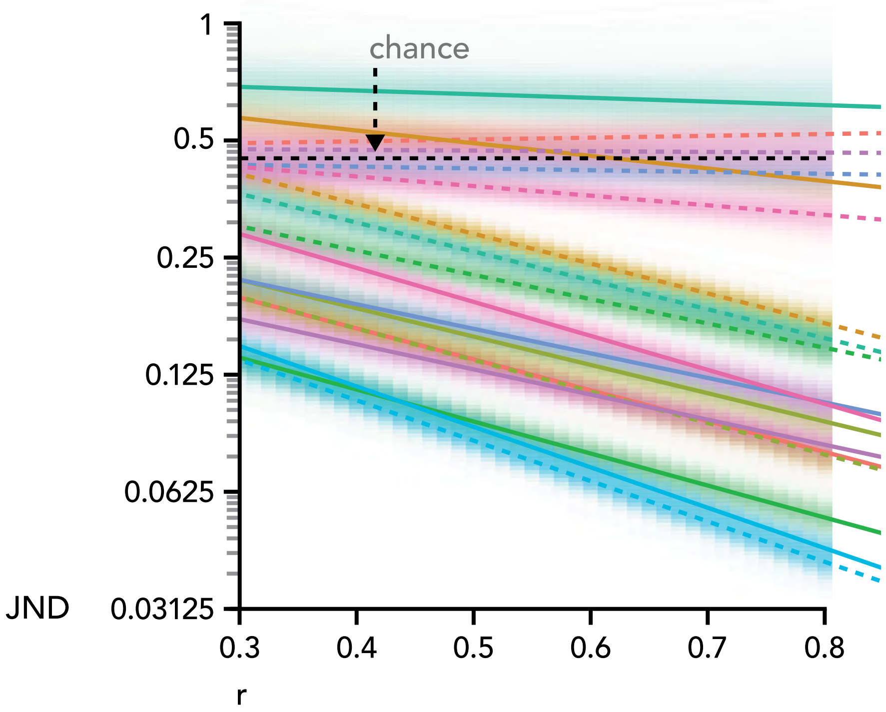
We also including random effects for participants so we can estimate between-participant variance.

Final model

1. The final Bayesian censored log-linear model gives us a posterior probability distribution over the mean log(JND) for each value of r.



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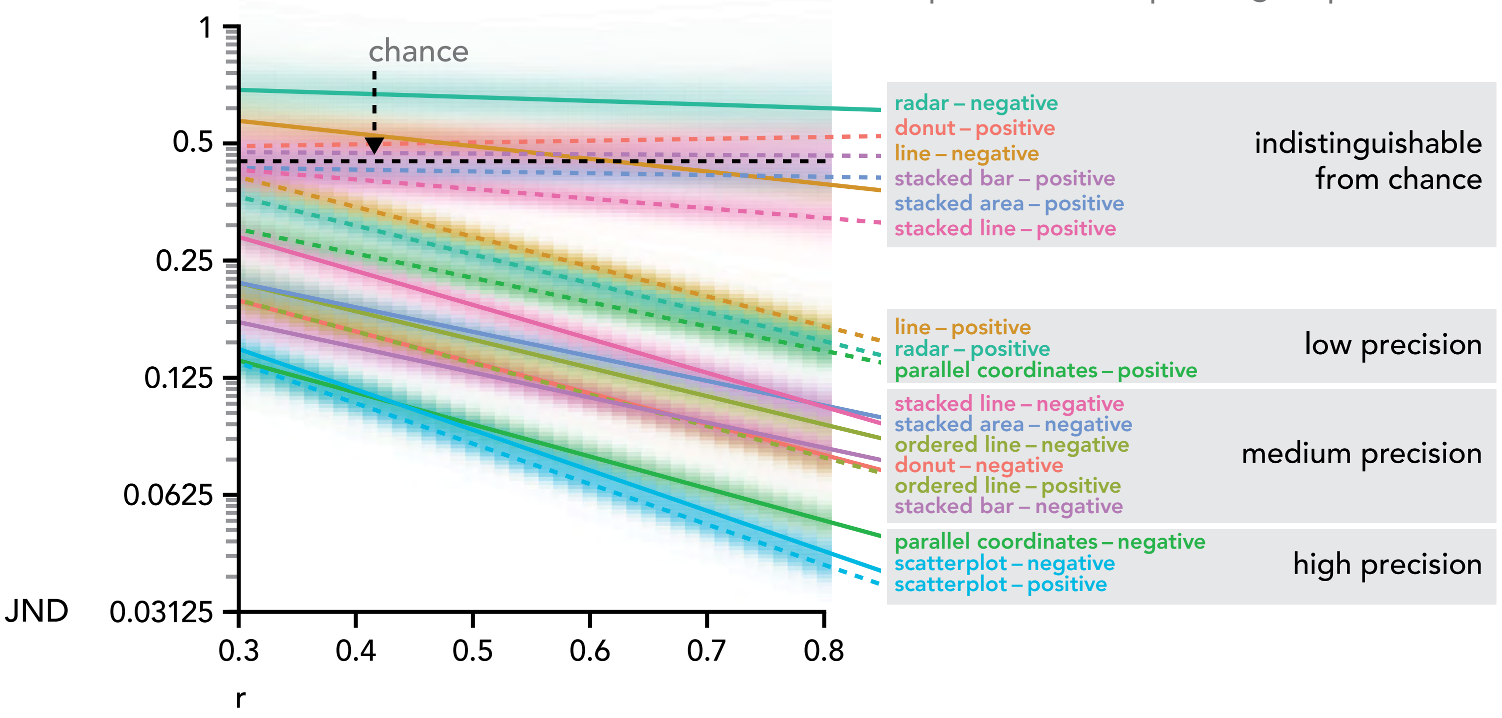
2. We rank and group visualizations based on how precise people's estimations of correlations are with them (lower expected JND implies higher precision)



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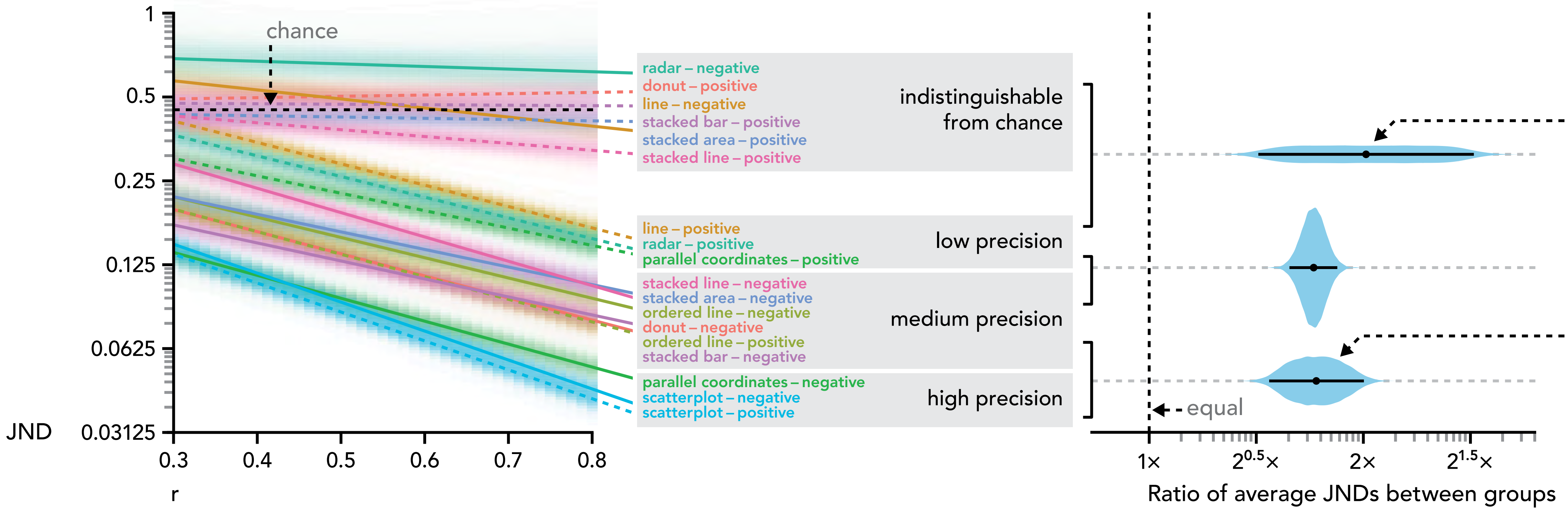

The low precision group is between **~1.5 and 3 times more precise** than the chance group.

The high precision group is between **~1.5 and 2 times more precise** than the medium precision group.

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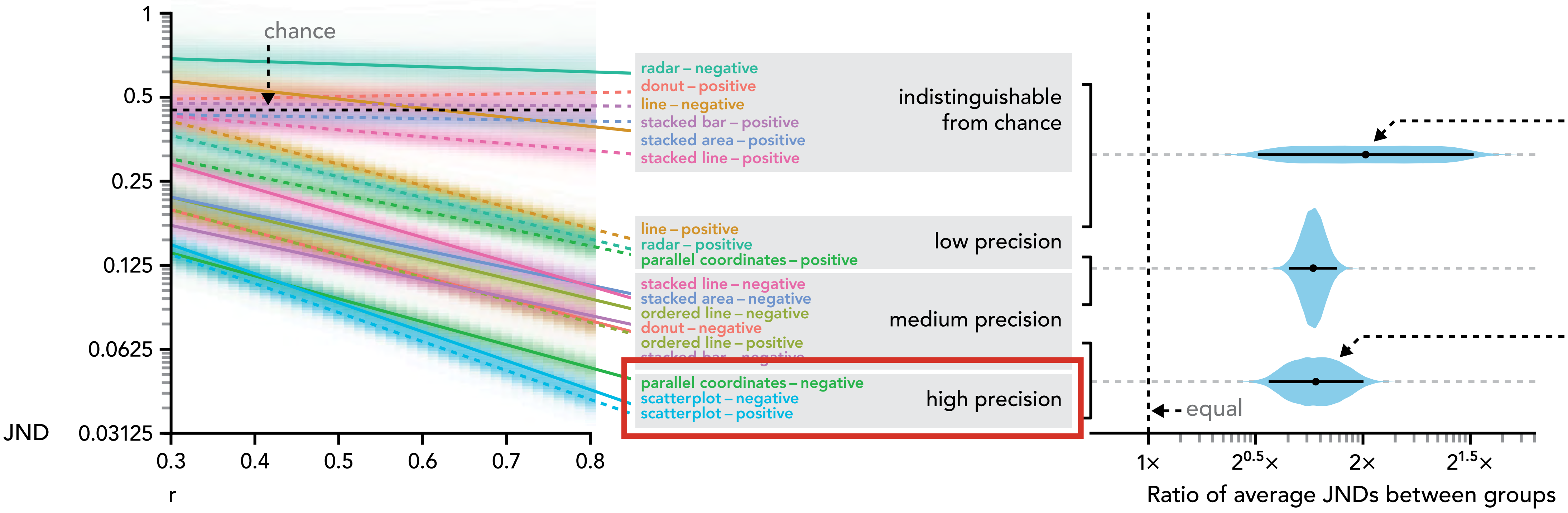

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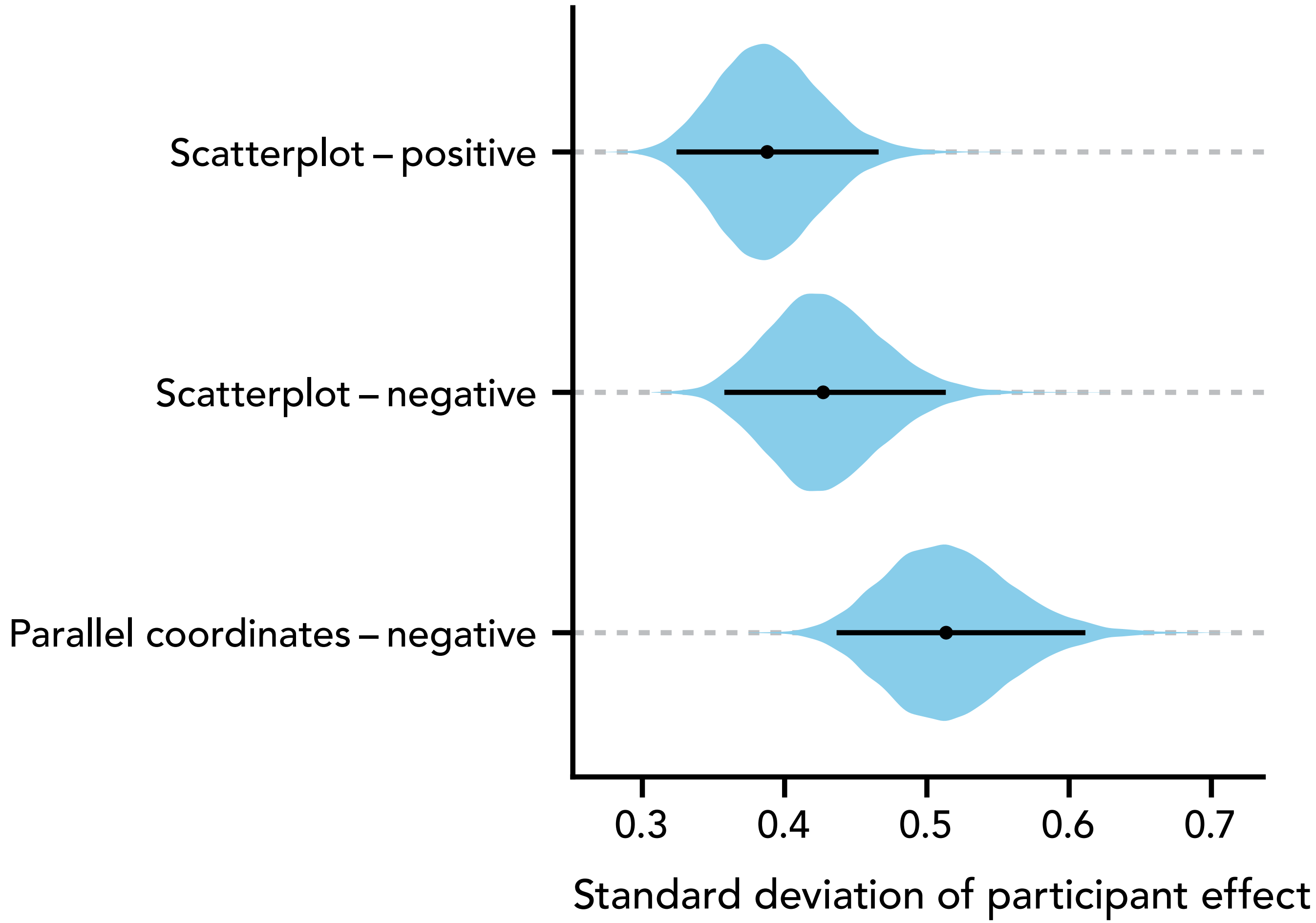
Between-participant variance



Discussion

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Scatterplots have low variance, work well on positively- and negatively- correlated data.

Considering variance and effect size beats p values for design recommendations.

Bayesian analysis helps us build on prior work.

Reproducibility is hard. What's the right approach?

Thanks!

github.com/mjskay/ranking-correlation

mjskay@uw.edu

mjskay.com