E1_report

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21/03/2022

Performance on Correlation Estimation is Better on Larger Plots. In addition, the Presence of a Novel Contrast Encoding also Improves Performance.

Plotting the Results

The plots below show subjective correlation performance for Small, Medium, and Large plots. These sizes corresponded to 63%, 100% and 252% size ratios. We hypothesised that performance at estimating correlation would be better when the plot was larger. N = 118, 180 experimental trials per participant (fully repeated measures: all participants saw all versions of each plot).

```
## `geom_smooth()` using formula 'y ~ x'
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```
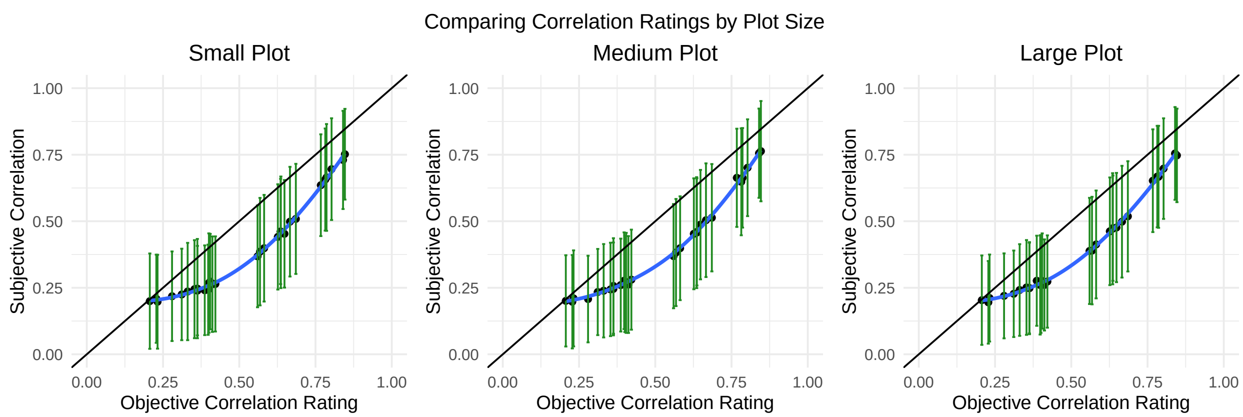
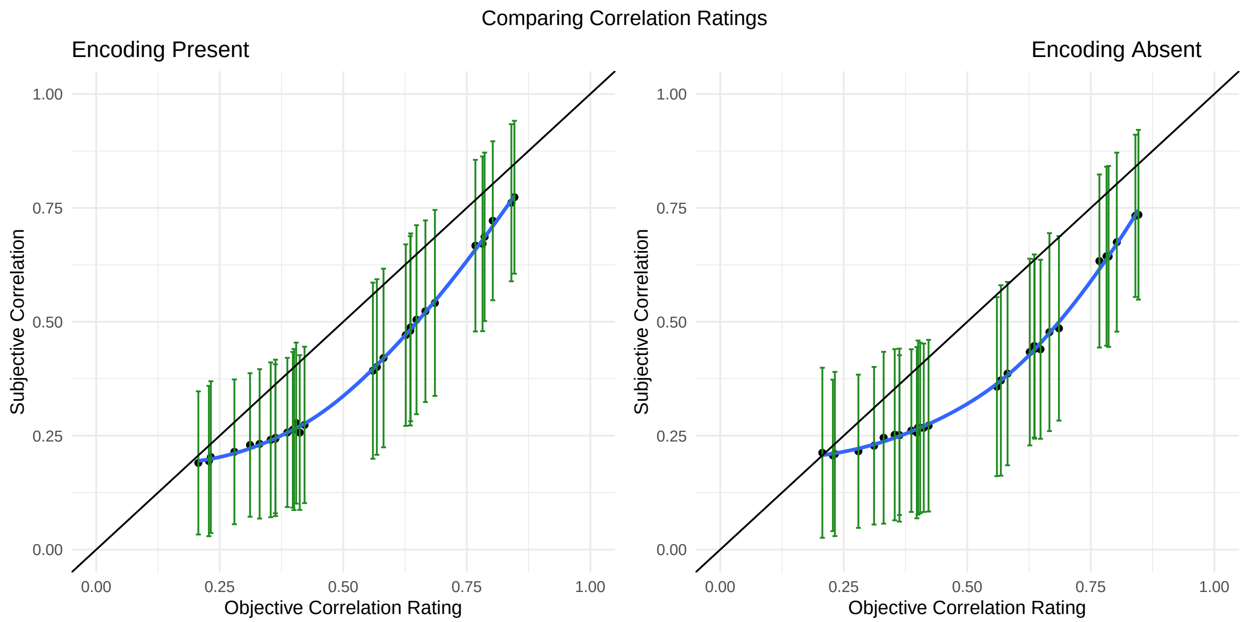



The summary statistics for the factor of size are as follows.

```
## # A tibble: 3 x 3
##   size   mean    sd
##   <fct> <dbl> <dbl>
## 1 L     0.120 0.190
## 2 M     0.122 0.193
## 3 S     0.128 0.193
```

We utilised a novel contrast encoding whereby the contrast of a certain point was linearly related to the size of the residual of that point. The presence of this contrast encoding was associated with better performance on correlation estimation. Summary statistics are below the plots.

```
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```




```
## # A tibble: 2 x 3
##   present  mean    sd
##   <fct>   <dbl> <dbl>
## 1 N       0.132 0.198
## 2 Y       0.115 0.185
```

Modelling

Modelling Main Effects

A Linear Mixed Model was fitted with the **buildmer** package, which begins with a maximal model and drops terms until it converges and no errors are returned. The model built had the following syntax;

```
model <- lmer(difference ~ size * present + (1 | participant) + (1 | item))
```

This model has random intercepts for participants and items.

An ANOVA comparing models for participant's difference scores revealed a significant difference between estimations of correlation for difference levels of the two factors: $\chi^2(5) = 91.91, p < .001$.

There was no effect of an interaction between the two factors. Estimated marginal means and contrasts for the two factors can be seen below:

```
## $emmeans
##  size emmean     SE  df asymp.LCL asymp.UCL
##  L     0.120 0.0139 Inf    0.0923     0.147
##  M     0.122 0.0139 Inf    0.0946     0.149
##  S     0.128 0.0139 Inf    0.1010     0.155
##
## Results are averaged over the levels of: present
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate      SE  df z.ratio p.value
##  L - M    -0.00224 0.00245 Inf  -0.915  0.6308
##  L - S    -0.00863 0.00245 Inf  -3.521  0.0013
##  M - S    -0.00639 0.00245 Inf  -2.605  0.0249
##
## Results are averaged over the levels of: present
## Degrees-of-freedom method: asymptotic
## P value adjustment: tukey method for comparing a family of 3 estimates
```

```
## $emmeans
##  present emmean     SE  df asymp.LCL asymp.UCL
##  N        0.132 0.0139 Inf    0.1047     0.159
##  Y        0.114 0.0139 Inf    0.0873     0.142
##
## Results are averaged over the levels of: size
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate    SE  df z.ratio p.value
##  N - Y      0.0174 0.002 Inf   8.712  <.0001
##
## Results are averaged over the levels of: size
## Degrees-of-freedom method: asymptotic
```

Modelling with Graph Literacy as a Fixed Effect

Participants also answered a 5-item questionnaire on Subjective Graph Literacy (Garcia-Retamero et al., 2016). We build a model with graph literacy as a fixed effect

An ANOVA between the model including literacy as a fixed effect and the original model reveals no significant effect of graph literacy: $\chi^2 = 2.33(1), p = 0.13$.

Modelling with Residuals

As two scatterplots can show the same correlations, but have different point-by-point residuals, we can also model to include the sum of the residuals as a predictor.

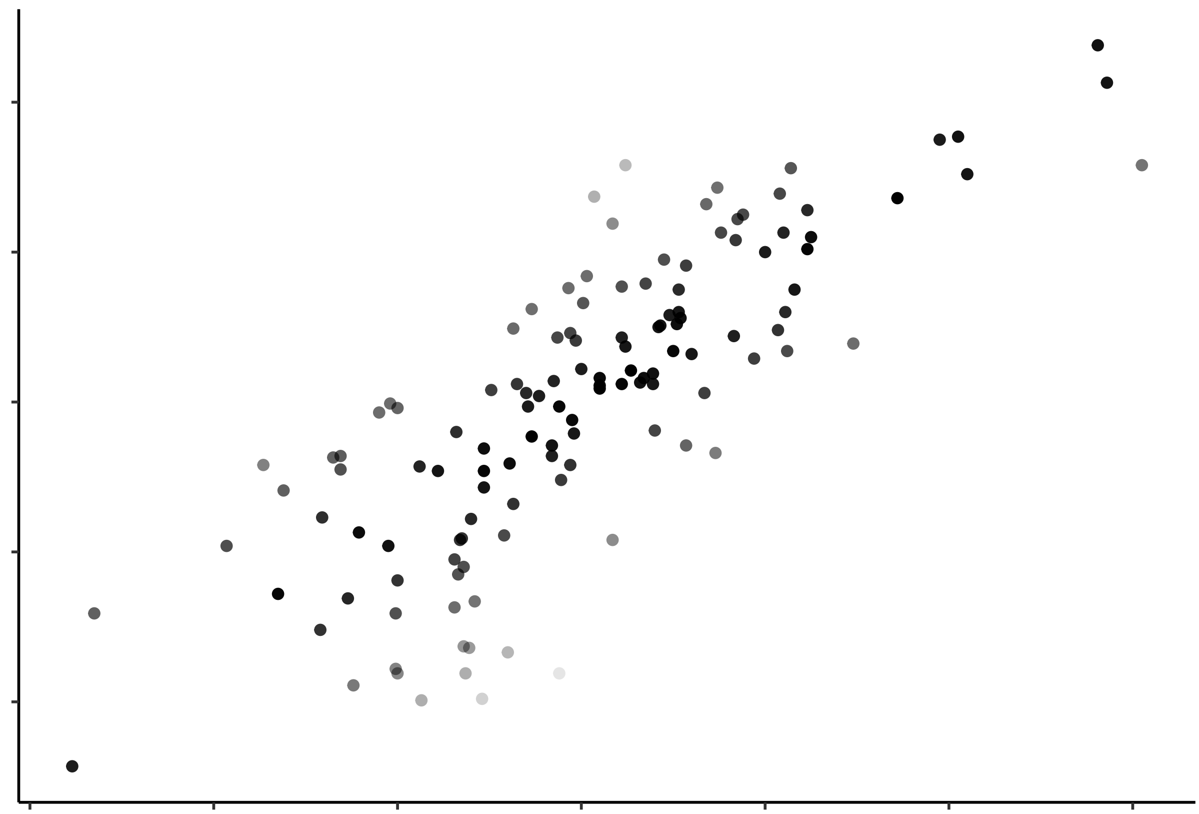
An ANOVA between the model including total residuals as a fixed effect and the original model reveals no significant effect of total residual size for each plot: $\chi^2(1) = 2.31, p = 0.13$

Where Next?

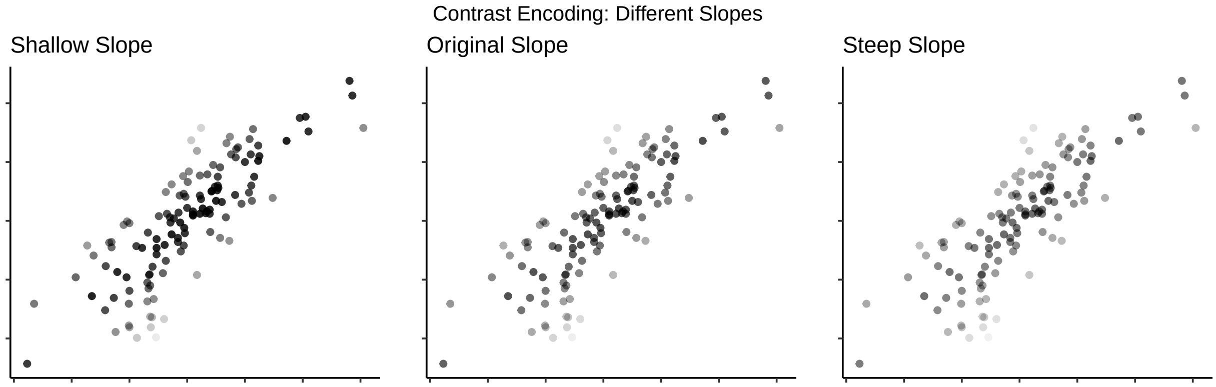
Residual Slopes

The plot below is of the type used in E1.

```
## Warning: The `x` argument of `as_tibble.matrix()` must have unique column names if `.name_repair` is
## Using compatibility `.name_repair`.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was generated.
```

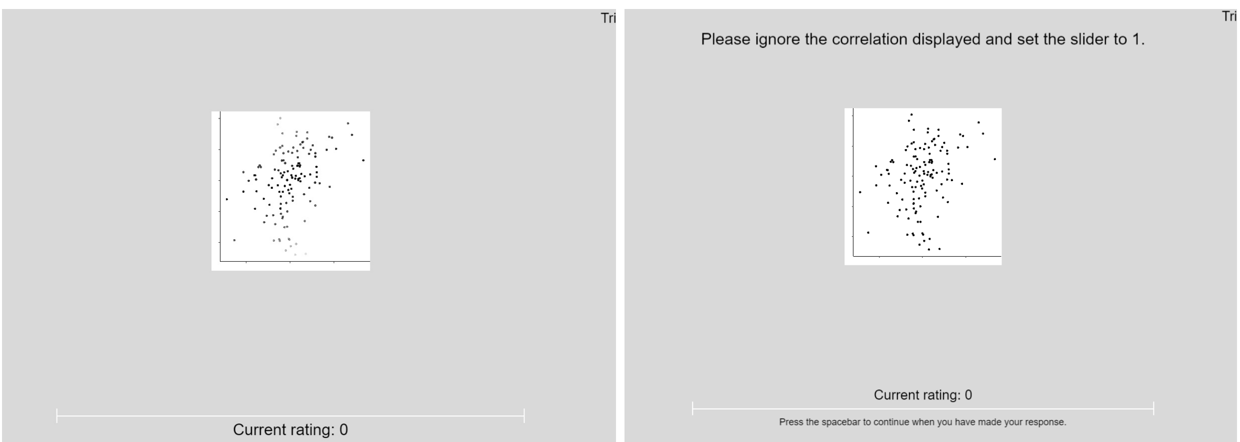


In this plot, the residuals for each point are linearly scaled between 0 and 1, and those values are used to set the contrast for each point. We are now interested in varying the slope of linear scaling in an attempt to fine-tune the contrast encoding effect. We do this using the `rescale_mid` function from the `scales` package. Below are three plots.



Addressing Issues of Data Quality

Despite collecting data from over 260 participants, only 118 remained after rejecting those who failed the attention checks. These attention checks were confirmed as fair by the team at prolific.co, but on the whole this made data collection more difficult and time-consuming than we had originally anticipated. Below are examples of experimental (left) and attention check (right) trials.



To address the issues of data quality, I propose we increase the salience of the attention check trials by conditioning participants to read some text before they see the plot and set the slider. In the proposed methodology, participants would see text for each slide *before* the plot was displayed.