1 Experiment 3.

[I'm assuming Joe will include some preamble for the experiment, but otherwise it should be fairly straightforward for me to churn out one anyway.]

1.1 Participants, Materials, and Procedure

Experiment 2 recruited 122 participants who each generated one set of four Alpha and four Beta category exemplars. Among these 122 generated category sets were 102 unique sets (i.e., they contained a unique collection of Alpha and Beta exemplars). Consequently, for Experiment 3, we recruited 102 participants with one participant presented with a different unique category set.

Participants observed four blocks of eight trials. Each trial began with the presentation of a fixation cross for 500 ms. This was followed by the presentation of one exemplar randomly sampled without replacement from the unique category set. Participants were tasked with assigning the presented exemplar to either the Alpha or Beta category with no time limit imposed. Feedback was automatically displayed for 2500 ms after each response.

1.2 Results

Overall accuracy of the participants was high, with a mean error rate of .19 (SD = .19). Error rates for each block are presented in Figure 1.

In the previous section (or Section X.X), we demonstrated that the best performing models were the two contrast models. In this section, our goal is to investigate if contrast is also important in category learning tasks.

It is also the goal of this paper to demonstrate that there is an association between the model's [justifying the errorvscat plot is harder than I thought] To compare the performances of each model, we analysed the correlation between each model's fit to a participant's unique category set and the participant's error rate. Intuitively, a well-performing model should be

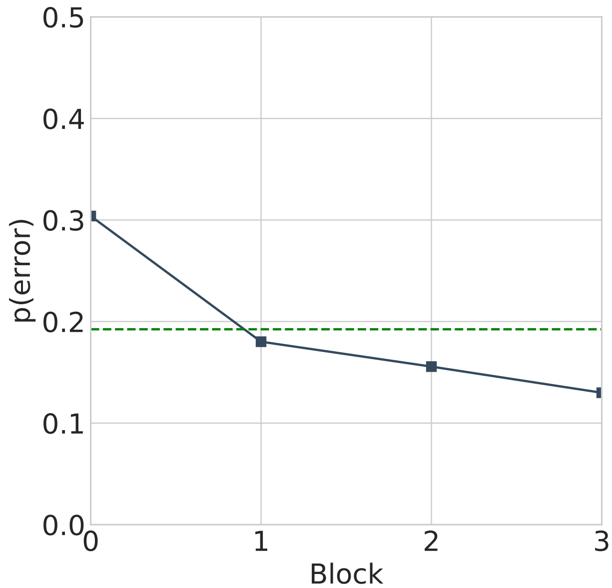

Figure 1: Average error rate for each successive block. Green discontinuous line represents the overall mean error rate.

able to closely fit (i.e., easily generate) A positive correlation would indicate that the model is We used the same set of optimised parameters found from Section X.X, with individual values for selective attention.

To emphasize the strong influence of contrast in maximizing the association between category generation and category learning, we computed the correlations over wide range of $\theta_{contrast}$ values, with the other parameter values of PACKER held constant at their optimized levels. As presented in Figure 3, the correlation quickly increases with increasing weight on contrast, reaching a plateau above values of around 4.0.

The specific reason for why contrast as implemented in PACKER is superior to contrast as implemented in the representativeness model is still not clear.

[Note Joe's comments on figure formatting (font size, remove redundant y-axes, etc)]

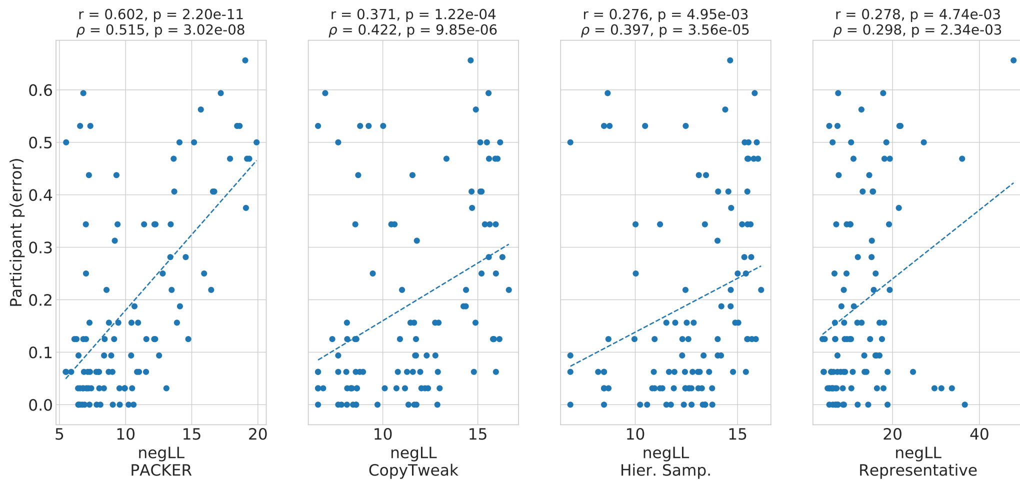

Figure 2: Correlation between observed participant error and model fit.

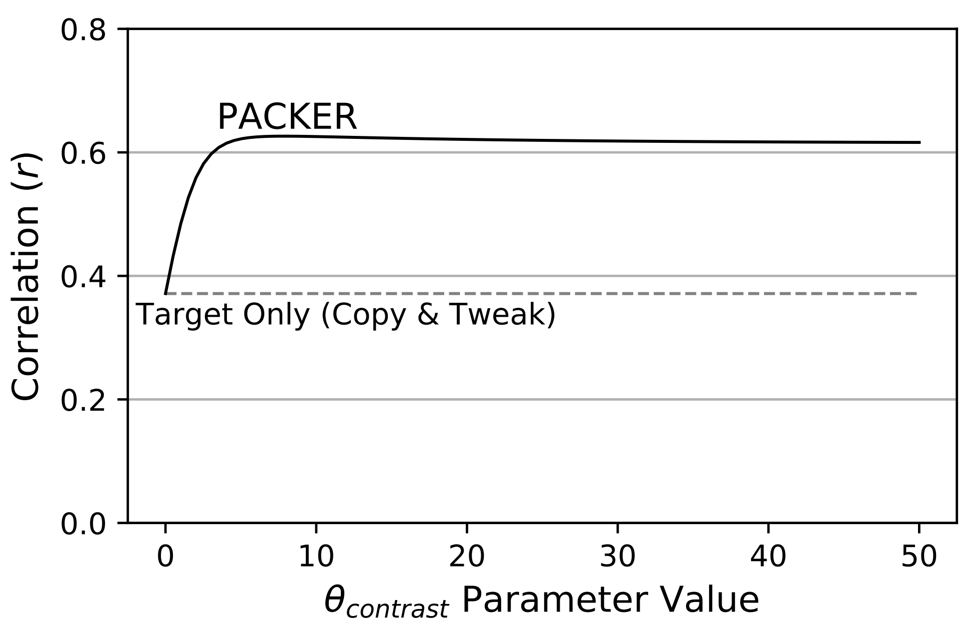

Figure 3: Correlation between PACKER's fit and participant error as a function of the $\theta_{contrast}$ parameter. To facilitate comparison, PACKER's other parameters (c, θ_{target}) were set to the best fitting values obtained for copy-and-tweak in Table **??**. Grey dashed line represents the correlation between Copy & Tweak's fit and participant error.