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CLASSIFICATION IMAGE WEIGHTS CAN DISCRIMINATE BETWEEN PROTOTYPE AND EXEMPLAR CATEGORY REPRESENTATIONS

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1. Introduction.

A fundamental issue in pattern recognition concerns understanding how image categories are represented in memory. Two important classes of perceptual categorization models assume either an *exemplar* or *prototype* category representation. Here, we demonstrate that the response classification technique[1] can be used to discriminate between exemplar and prototype category representations.

2. Models.

Exemplar Model. A representative exemplar-based categorization model is the Generalized Context Model (GCM)[2]. According to the GCM, the probability of choosing category A is given by:

$$P(A\mid i)=\frac{\sum s_{ia}}{\sum s_{ia}+\sum s_{ib}} \tag{1}$$

where Ss_{ia} and Ss_{ib} are the summed similarities of item *i* to stored exemplars of the stimuli in categories A and B, respectively. The similarity between item *i* and a given exemplar is assumed to be an exponential decay function of their psychological distance:

$$s_{ij}=e^{(-cd_{ij})} \tag{2}$$

where d_{ij} is the psychological distance between item *i* and exemplar *j*, and *c* is an overall sensitivity parameter. The distance between exemplars *i* and *j* is given by:

$$d_{ij}=\sum_{m=1}^{M} w_m\left|x_{im}-x_{jm}\right| \tag{3}$$

where x_{im} and x_{jm} are the values of exemplars *i* and *j* on dimension *m*, w_m is and attention weight given to dimension *m*, and *M* is the number of dimensions along which the stimuli vary.

Prototype Model. The major difference between a prototype and exemplar model is that observers are assumed to use a single summary representation for each category[3]. Thus, in a prototype model, the probability of choosing category A is given by:

$$P(A\mid i)=\frac{s_{iA}}{s_{iA}+s_{iB}} \tag{4}$$

where s_{iA} and s_{iB} are the similarities (calculated as in (2)) of item *i* to the stored prototypes for categories A and B, respectively.

Template Matching Exemplar and Prototype Models. According to standard template matching models of pattern recognition, an observer determines a stimulus category by computing the similarities between item *i* and each of a set of noisy templates T_j.

A Bayesian exemplar template matching model assumes observers use all stored templates from a given category to determine the likelihood that item *i* came from category A:

$$L(A\mid i)=\sum_j e^{(-\frac{1}{2\sigma^2}\|i-T_{ja}\|^2)} \tag{5}$$

where T_{ja} is the j^{th} template from category A. The observer then chooses the category that yields the highest likelihood. This turns out to be the statistically optimal rule for our task (see below)[4].

A prototype template matching model is identical to the exemplar template matching model, with the exception that the item is compared to only a single representative template for each category:

$$L(A\mid i)=e^{(-\frac{1}{2\sigma^2}\|i-T_a\|^2)} \tag{6}$$

3. Task.

Observers were asked to categorize four stimuli into two categories. The stimuli were four white squares that could appear at one four possible fixed locations relative to fixation: top left (TL), top right (TR), bottom left (BL) and bottom right (BR) (see Figure 1). One square was chosen randomly on each trial and shown for 500 ms, and the observer's task was to determine whether the square had appeared above or below fixation (category A or B in Figure 1, respectively).

Each location where the squares could appear was corrupted by a 4x4 grid of high contrast Gaussian white noise (see Figure 2). The contrast of the signal was manipulated across trials with a staircase to maintain 71% correct performance.

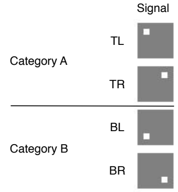

Figure 1: Categories and Signals

Figure 2: Example Stimulus (signal is at the bottom right)

4. Simulations.

Because of the exponential nonlinearity described in (5), the exemplar model predicts that noise presented to the template in the location where the signal is present should typically have a greater influence on observer's decisions than the signal-absent location in that category. However, this is not the case for the prototype model, because only a single template is used within each category. Thus, we would predict a differential weighting across stimulus locations within each stimulus-response bin of a classification image for an exemplar model but an identical weighting across locations within each bin for a prototype model.

We measured classification images for simulated observers in our task using the decision rules described in (5) and (6). Each simulated observer performed 50,000 trials. The exemplar model used the raw signals describe in Figure 1 as templates. The prototype model used the sum of the individual templates in each category as templates (Figure 3). Figures 4 and 5 show the simulation results. In Figure 4, each group of 4 squares shows the correlation between the noise contrast and the observer's responses for the corresponding stimulus-response combination. Figure 5 summarizes Figure 4 by contrast reversing and/or flipping each bin to be consistent with the 'signal = top-left, response = top' bin and combining the data to form a single 4-square image. The left panels show the raw combined images and the right panels show the same images with the pixels averaged within each square. As predicted, the exemplar observer weights the signal-present location more than the signal-absent location within the category where the signal occurred.

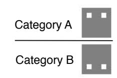

Figure 3: Prototype Model Templates

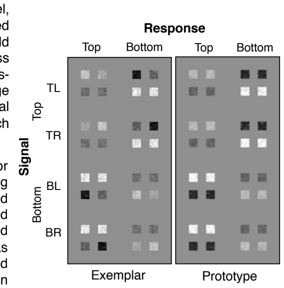

Figure 4: Classification Images for Simulated Observers

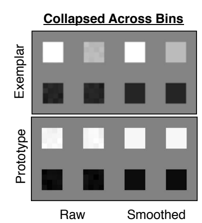

Figure 5: Combined Classification Images

5. Human Data.

We conducted the same experiment with 4 human observers (2 authors, 2 naïve). Each observer participated in 4,000 trials. Figure 6 shows the classification images generated by combining the data from all 4 observers (16,000 trials). Figure 7 shows the collapsed classification images computed as in Figure 5 for 2 representative observers (rows 1-2) and the combined data for all 4 observers (row 3).

These data show that, like the exemplar model, human observers weighted signal present locations more than signal absent locations. We quantitatively tested the predictions of the exemplar and prototype models by comparing the ratio of mean correlation values obtained in the signal present vs. signal absent locations for each of the model observers as well as the human observers. Simulations were conducted for each model observer to determine the predicted mean and variability of correlation ratio values produced by classification images constructed from sets of 4,000 trials. Figure 8 shows the results of this analysis. These data show that the predicted correlation ratios obtained using the exemplar rule were nearly identical to the correlation ratios obtained from human observers.

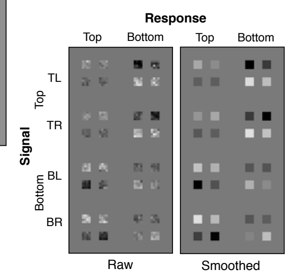

Figure 6: Classification Images for Human Observers (combined data)

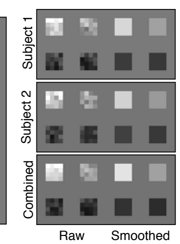

Figure 7: Collapsed Classification Images

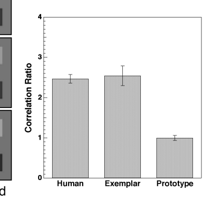

Figure 8: Correlation Ratios for Humans and Models

6. Conclusions & Future Directions.

- Our classification image results are quantitatively predicted by an exemplar model of visual categorization and are inconsistent with the predictions of a prototype model.
- Can we apply this technique to more complex / interesting categorization tasks?
- Can we manipulate the conditions / instructions to induce the use of a prototype strategy?

7. References.

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