Lateralisation of Exemplar and Prototype Controls in Category Learning

HUV886: Special Module in Cognitive Psychology

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Knowledge Representation

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Categories are one kind of knowledge structure which enable a more compact mental representation of things that share a significant number of characteristics or attributes, and efficient comparison across categories

Similarity therefore becomes an important notion to describe categories

Models of Category Learning

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Prototype model says that when categorising a new object, our cognitive system compares it to prototypes of various categories, thus assigning it to the one whose prototype is the closest (in similarity) to the new object

Which Model Works Better?

- Cognitive scientists have designed experiments in support of either of the two, coming up with contrasting results: while some claim that exemplar approach is better in explaining atypical and abstract categories, others claim prototype approach better explains large-sized categories
- Some researchers have concluded that people use both models of learning, with prototypical model being used in early stages and exemplar model in later stages of learning, to handle class exceptions

Objective 1

To provide a powerful platform for testing these contradictory hypotheses, and reconciling them through a general mathematical framework.

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Categorical representation appears to be different across the hemispheres: while the left side retains abstract, categorical or prototypical information, the right side retains specific characteristics of the exemplars

Marsolek's Experiments (1995)

- The stimuli set a consisted of eight prototypes, an exemplar training set b and testing stimuli set c made by distorting class prototypes.
- Training followed by a speeded test classification task, using all three stimuli set (a, b and c). The stimuli was flashed in either the left or the right visual field.

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- Training followed by a speeded test classification task, using all three stimuli set (a, b and c). The stimuli was flashed in either the left or the right visual field.
- When classifying the training stimuli set b, which they had already studied, the subjects were faster when the stimuli were presented in the left visual field (or to the right hemisphere), and vice-versa for the prototype stimuli set a.

Objective 2

To test the hypothesis of lateralisation under general stimuli settings

Hypotheses

Hypothesis 1 There exists a **lateralisation** of the cognitive function of **categorical representation, learning, as well as inference** in the brain. While the left hemisphere stores and operates under the prototypical model, the right hemisphere operates under the exemplar model, giving rise to a mixed model of categorical knowledge representation.

Hypotheses

Hypothesis 2 The exemplar model is favoured over the prototype model for smaller category sizes. Given that Hypothesis 1 is true, and as learning of and inference from the two categories progresses, there exists an epoch when **cognitive control shifts from the prototype model to the exemplary model**, that is, the left hemisphere begins to dominate the right hemisphere in categorical knowledge representation.

Experiments in Literature

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- Independence of features for estimating psychological distance
- We use the Divided Visual Field paradigm: controversial!

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2. For generating images for a category, warp its prototype "randomly" using a spline transform (at n points within a window w)
3. Rotate the image by a random angle θ
4. Repeat for all exemplars of the required category

(a) Prototype A

(b) Prototype B

(c) Few Exemplars for Category A

(d) Few Exemplars for Category B

Figure: Sample Kanji Characters used in Experiment 1 of this study

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- First part was under a traditional training-testing paradigm, with a total of 80 non-repeating samples
- Second part was under a simultaneous learning and testing paradigm, with a total of 80 non-repeating samples
- Experiments were carried out eventually with 50 subjects (all males, largely right-handed) succeeding in finishing the experiment completely

Evaluating Image Similarities

1. A representative image set I of all the images (corresponding to the particular experiment part being considered), each of them of size 256×256, was created
2. Principal Component Analysis was used to reduce the dimensions of the image set to a small number of 8; quite advantageously, PCA ensure that these dimensions are orthogonal and thus independent: $I_{n \times 65536} \rightarrow \hat{I}_{n \times 8}$

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3. Let d_{ij} represent the Euclidean distance between images i and j in the PCA space; we can define their similarity simply as:

$$s_{ij} = e^{-cd_{ij}}$$

where c is a parameter of our model

Bayesian Cognitive Model

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- Say the subject is operating under one of the two models of category learning, (what is called a hypothesis in the theory of model selection): either h_1 or h_2
- If we know $P(X|h)$, then we can find out $P(h|X)$ by using Bayes' Rule:

$$P(h = h_1|X) = \frac{P(X|h = h_1) \cdot P(h = h_1)}{\sum_{i=1,2} P(X|h = h_i) \cdot P(h = h_i)}$$

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- What about model parameter c?

$$P(h = h_1 | X, \hat{c}) = \frac{P(X | h = h_1, \hat{c_1})}{\sum_{i=1,2} P(X | h = h_i, \hat{c_i})}$$

$$\hat{c_i} = argmax_{c \in dom(c)} P(X | h = h_i, c)$$

Bayesian Cognitive Model

Quantifying Probability Distributions for either hemispheres

- For the exemplar model:

$$P(A|i) = \frac{\sum_{a \in A} s_{ia}}{\sum_{a \in A} s_{ia} + \sum_{b \in B} s_{ib}}$$

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- And we "observe" X from the actual correctness of the subject's answers

Bayesian Model Selection Results

- Filters: confidence threshold (X), accuracy threshold (0.5), significance threshold (0.75)
- Eventually, only 7 hypotheses instances survive:

Hypothesis	**Frequency**
LVF-Exemplar	2
LVF-Prototype	1
RVF-Exemplar	1
RVF-Prototype	3

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But perhaps, model selection is not very clear, and there are degrees of their development

Bayesian Model Selection Results

Without a significance threshold:

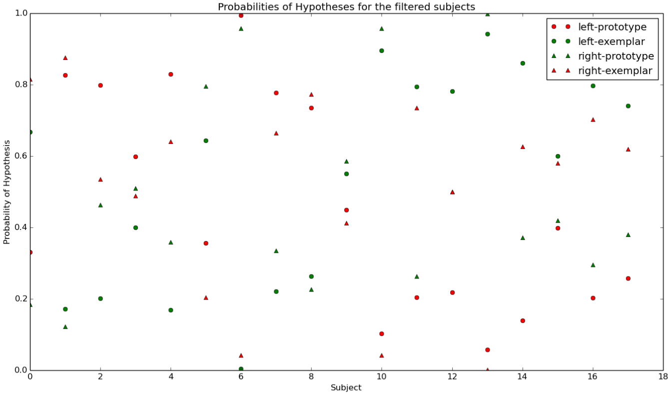

Figure: Variation in "Lateralisation"

Bayesian Model Selection Results

Without a significance threshold, 36 hypotheses instances survived:

Hypothesis	**Frequency**
LVF-Exemplar	11
LVF-Prototype	7
RVF-Exemplar	12
RVF-Prototype	6

Average Probability Distribution Analysis

- Treat the "probability of correctness" as a random variable over a space spanned by individual subjects
- Find the probability distributions for the 4 possible hypotheses, and use KL Divergence to quantify their semblance to the actual probability distributions

$$D_{KL}(P||Q) = \sum_{i} P(i) log \left(\frac{P(i)}{Q(i)} \right)$$

APD Analysis

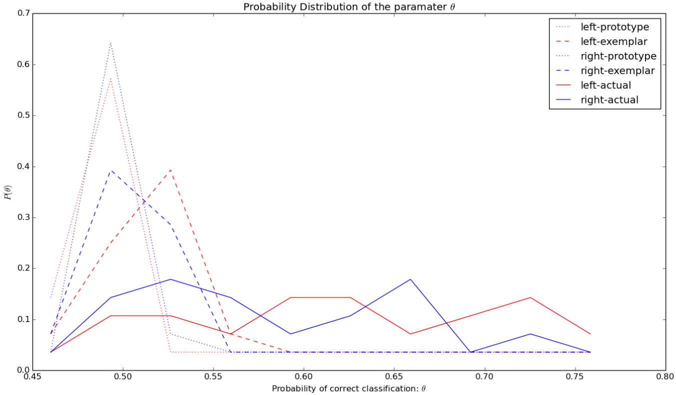

Figure: APD Analysis as a "Model Fitting"

APD and KL Divergence Analysis

Hypothesis	**Divergence**
LVF-Exemplar	0.771
LVF-Prototype	1.231
RVF-Exemplar	0.556
RVF-Prototype	1.018

(Note that smaller the divergence, better is the distribution fit)

Reaction Time Trends

- To test hypothesis 2: plot the reaction times of the LVF and RVF stimuli during simultaneous learning and testing phase (after low pass filtering)
- Given that the first hypothesis is true, a switch in control of models should be evident in the resource constraints, and thus the response time

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- Since hypothesis 1 doesn't entirely stand proven, we plot these only for some of the surviving hypotheses instances
- We observe some sort of "switching over" between the two hemispheres

Reaction Time Trends

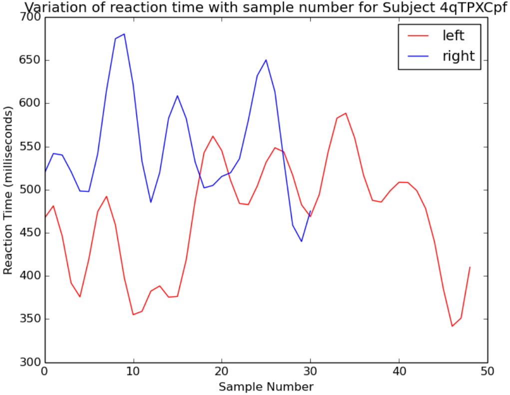

Figure: LVF-Prototype Reaction Time Trend

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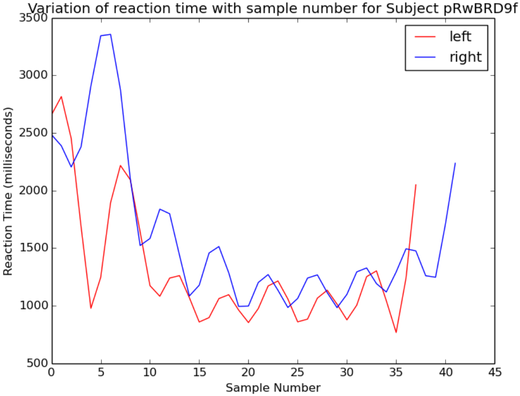

Figure: LVF-Exemplar RVF-Exemplar Reaction Time Trend

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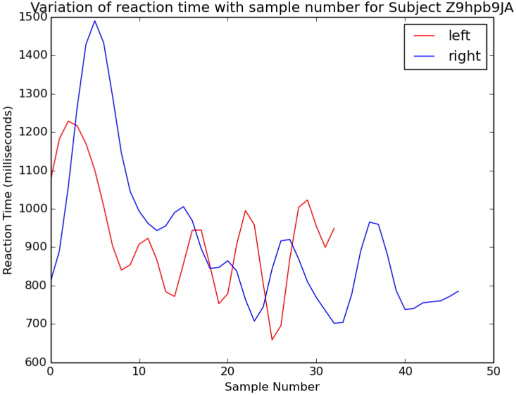

Figure: LVF-Exemplar RVF-Prototype Reaction Time Trend

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- It provides a more sound design methodology and a general mathematical framework to pursue more such studies, after careful curation of the datasets
- **More (non-corrupt) data points are required to populate the hypotheses with more confidence**

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