

What Can We Learn in Perceptual Learning?

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Previous studies in perceptual learning have found different results in amount of transfer of learning between tasks (specificity). These studies also found different results for learning that takes place in different tasks. In this study, we wanted to understand what the subject is learning. Thinking in a statistical-learning (Bayesian) framework, we understand learning by defining the error function,

$$E(G, C, D) = \int \int \int_{I R S} P(S | I, d(R : D)) P(R | I, G) P(I | C) L(S, I, d(R : D))$$

where G, C, and D are parameters, I is input, R is response, S is supervisor critique after the system decides d(R:D), P indicates probability, and L is the loss function, indicating how much the system pays if it makes the wrong decision. Learning is modeled through error minimization as,

$$(G^*, C^*, D^*) = \arg \min_{G, C, D} E(G, C, D)$$

These three parameters describe what kind of learning can take place in a given training task. We can learn the prior distribution (Parameter C), the likelihood function (Parameter G), the decision rule (parameter D), or a combination of these different functions. Mathematical analysis suggests that they can be learned through the following three strategies: First, the system could learn only the decision rule, by sampling the environment, without attempting to learn the prior distribution. Second, the system could learn the optimal prior and the decision rule simultaneously (or the likelihood function or both). Third, the system could only learn the prior and compute from it the decision rule.

A task of motion segmentation was used in psychophysical experiments to explore what kind of learning takes place in perceptual learning. We obtained results in difficult and easy versions of the task. Results suggested that we learn a different set of the above functions in different situations.