Explaining Eye Movements During Learning as an Active Sampling Process

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Abstract

Savage [1] proposed analyzing active sampling problems as decision problems in which the goal is to maximize expected utility, relative to a probability distribution describing one's beliefs. In the past 20 years this framework has been applied to several psychological tasks [2]. We use this framework to model eye movements in a concept formation task [3], [4].

Introduction

In Shepard's classic concept learning task [3], participants gradually learn which of eight objects are consistent with a category unknown to them. The objects comprise each of 2^3 possible combinations of three binary stimulus dimensions. Objects include large black circle, small black triangle, small white circle, and so on. In each trial, the subject is shown a random object, guesses whether the object is consistent with the true concept, and receives feedback. This continues until the subject achieves near-perfect classification accuracy or a maximal number of trials is reached. Several theories make specific claims about how selective attention to different stimulus dimensions, for example shape or color, is deployed throughout learning. Rehder & Hoffman [4] devised a new version of Shepard's concept learning task to provide direct evidence of selective attention. Rehder & Hoffman separated the stimulus dimensions spatially, representing each binary dimension as a character that could take one of two values ($ or ¢, x or o, ? or !), at each vertex of a large triangle on a computer screen. Three primary findings were reported:

1. Early in learning, all stimulus dimensions are fixated.
2. There is gradual improvement in classification accuracy throughout learning.
3. After the concept is mastered, eye movements become efficient, restricted to only the dimensions needed to classify objects given the true concept.

Rehder & Hoffman suggested that RULEX [5], a prominent rule-based model of category learning, and ALCOVE [6], a prominent similarity-based model, each appeared to be contradicted by different features of their data, but did not specify a model to account for their data.

We show that a concise probabilistic model can account for the different amounts of learning required to master concepts in the classic task. Our generative Bayesian model gives higher probability to concepts that a priori criteria judge to be less complex, and that human subjects find easier to learn. Information obtained by fixating particular stimulus dimensions is assimilated in an optimal Bayesian manner. To calculate the usefulness of each possible eye movement we use a principled utility function, based on information theory [7], taking into account all learning to date. Results show that the eye movement model accounts for eye movement patterns observed both early and late in learning in the eye movement task. We further propose that this task exemplifies Helmholtz' idea [8] of vision as unconscious inference.

References

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