Cue Validity in Category Learning

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Introduction

Simple Bayesian classifiers are a commonly used model of categorization. However, certain characteristics of human performance are not captured by traditional Bayesian models. Examples of such phenomenon are inverse base rates and base rate neglect. This report examines the simple (naive) Bayesian model of these phenomenon along with two variants, one which ignores base rates and one which includes a cue validity weighting of the attributes.

These three models are applied to two data sets (Kruschke, 1996; Experiments 1 & 3). The experimental task is diagnosing a disease given a set of symptoms. Participants are trained on a set of four diseases, two common and two rare. The common diseases have a base rate three times that of the rare diseases. In Experiment 1, each disease has two symptoms, one which is only associated with it and one which is associated with both a common and rare disease. Hence three symptoms are used to predict two diseases. Thus there are four possible diseases being predicted by six symptoms. After training, the participants are required to diagnose novel combinations of these symptoms.

Experiment 1 replicates the inverse base rate phenomena reported by Medin & Edelson (1988). Inverse base rate occurs when participants are given a pair of symptoms, each being perfect predictors of a common and a rare disease. On the majority of trials, participants appear to ignore base rates by assigning the symptom pair to the rare disease.

Experiment 3 is similar to Experiment 1 except that one of the common diseases shares a rare disease's symptom. The symptom occurs equally in both the rare and common diseases. This design replicates the base rate neglect phenomena reported by Gluck & Bower (1988). Base rate neglect occurs when participants who are given a symptom that equally predicts two diseases, choose the rare over the common disease.

Bayesian Models

These two data sets are modeled using three variants of Bayesian models: a simple (naive) Bayesian, a simple Bayesian without base rate information (i.e., $P(C_k)$ removed), and a Bayesian in which each symptom is weighted by the cue validity, $P(C_k|A_i)$. A symptom that is concentrated in one category is more diagnostic of that category than a symptom that is spread out over a number of categories. This account generates the following expression:

$$P(C_k)\prod_{i=1}^{n}\frac{P(C_k|A_i)P(A_i|C_k)}{P(A_i)}$$

Discussion

Tables 1 and 2 both show that a Bayesian model modified by ignoring base rates does a poor job at fitting the data, accounting for 53% and 52% of the variance in Experiments 1 and 3. The Bayesian model which includes base rate information accounts for 75% and 68% of the variance. These results suggest that base rates are not being ignored (consistent with Kruschke's views). The Bayesian model with cue validity fits the data better than the other two models, accounting for 93% of the variance in Experiment 1 and 81% of the variance in Experiment 3. Thus, this research supports the inclusion of cue validity in order to more accurately account for human categorization.

Table 1: Model fits for Experiment 1, R^2 and Root Mean Squared Deviation (RMSD)

Model	R^2	RMSD
Bayes: No Base Rate	0.5305	0.2462
Bayes: Naive	0.7583	0.1582
Bayes: Cue Validity	0.9302	0.0953

Table 2: Model fits for Experiment 3

Model	R^2	RMSD
Bayes: No Base Rate	0.5208	0.2355
Bayes: Naive	0.6758	0.1829
Bayes: Cue Validity	0.8096	0.1465

References

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