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Multiple-Cue Probability Learning

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Synonyms

Function learning; Lens model; Probabilistic categorization; Weather prediction task

Definition

Multiple-Cue Probability Learning (MCPL) is an experimental paradigm concerned with how well people can learn imperfect relationships between cues and outcomes. In a typical MCPL task, participants are shown an array of cues each of which predicts a particular outcome with some probability; usually this probability is less than unity, mirroring the imperfect nature of cues in the natural environment. The cues are usually instantiated as simple perceptual stimuli, which can be either discretely (often binary) valued, such as color – a given cue might be a red or green, for instance – or stimuli can be comprised of continuously valued dimensions – such as bars of different lengths. The former case with discrete cues is typically referred to as *nonmetric* multiple-cue probability learning (NMCPL), and the latter case with continuous cues is termed *metric* multiple-cue probability learning. Outcomes or responses are typically discrete (e.g., press a button when shown cue A, but do not press the button when shown cue B) or categorical (press the button for category X or Y, depending on the cue configuration); however, some variants of the MCPL task use continuous outcomes. Depending on the types of cues and outcomes, MCPL is often very similar to other concept-learning domains; a classification of the most popular domains is shown in Fig. 1. The key distinguishing element of MCPL is the fact that the corrective feedback that follows each response is probabilistic rather than deterministic; those cells are shaded in Fig. 1.

As an illustration of MCPL, consider the weather prediction task shown in Fig. 2 (the task is called a weather prediction task because the outcomes are usually given arbitrary names such as RAIN and SHINE). The stimuli are comprised of four cues. Each cue can either be present or absent on each trial, and for the present example, only one shape may be presented on each trial. Each cue is represented by a different shape that can be used to predict an outcome, in this case with probabilities equal to 0.45, 0.55, 0.80, and 0.40 for outcome X, for the four cues, respectively. (Note that in this example, there are only two possible outcomes. The opposite outcome, call it Y, is predicted with one minus the probability of outcome X; in this example, P(Y) is 0.55, 0.45, 0.20, and 0.60 for the four cues, respectively.) The cues vary in how well they predict the outcomes, if a participant responded with X every time she were shown a triangle, she would be correct 80% of the time.

Unlike other learning paradigms, MCPL does not primarily focus on learning strategies but on how closely people's behavior matches the relative information available in the cues. For example, of the four cues in Fig. 2, the triangle is a more valid predictor than the other three symbols; higher levels of accuracy can be attained by using only this cue to guide decision making and ignoring the other less valid cues. The core concept of *validity* refers to how well a cue predicts a given outcome; cues with high validity are good predictors of an outcome whereas cues with low validity give little or no information about what the outcome might be. In MCPL, primary importance is placed on how well people *utilize* cues of different validities; that is, do people base their responses and decisions on cues with greater validity? And how well does observed cue utilization compare with optimal cue utilization?

The optimal strategy for the example in Fig. 2 is to always respond X when a triangle is present and respond Y when a triangle is absent; although this response strategy, known as "maximizing" cannot avoid the inevitable error arising from probabilistic feedback, it can at least maximize accuracy. However, people typically deviate from this optimal strategy and instead match their response proportions to the underlying probabilities.

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That is, when shown a triangle, people tend to respond X only 80% of the time (reducing accuracy from a possible 80% to 64%); when shown a plus sign, they respond with X only 55% of the time; and so on. Probability matching is commonly observed in decision-making and categorization tasks. One way to examine probability matching is by computing a measure of achievement, such as the correlation between response proportions and the underlying feedback probabilities.

Theoretical Background

MCPL originated as a method to apply Egon Brunswik's ideas about probabilistic functionalism, which were initially developed to study visual perception, to learning and behavior. Probabilistic functionalism is the idea that the external environment and internal perceptions of that environment are variable, and that to function successfully in a variable environment, an organism must learn to utilize only reliable and valid cues (Brunswik 1943). Probabilistic functionalism thus emphasizes the imperfect nature of the environment (and organisms). Foremost among Brunswik's concerns were that psychological laboratory experiments should use stimuli and feedback which represent the probabilistic nature of the environment and that the external environment should be given as much prominence in psychological theory as the organism in that environment. The former concern has clear reverberations in modern concerns about ecological validity; the latter concern predated rational approaches to cognition (e.g., Anderson 1990), but was perhaps better advocated by Brunswik's contemporary, James Gibson, culminating in ecological psychology and dynamical systems approaches to perception, cognition, and action.

Important Scientific Research and Open Questions

MCPL is related to several other domains, and many tasks which are currently popular (such as function learning) have direct precursors in the MCPL literature. However, the use of MCPL as a tool for studying learning declined substantially in the late 1970s, concurrent with a shift in cognitive psychology toward emphasizing computational modeling of the processes and representations underlying learning behavior (cf. Estes 1976). MCPL's preoccupation with simple measures of achievement ("how well can people learn?") was abandoned in favor of measures of strategy and prediction ("what and how do people learn?"). However, several important studies have thus sought to differentiate computational models using NMCPL.

In NMCPL, two sources of cue information have been studied extensively: cue validity and cue salience. Salience refers to some intrinsic property of the cue which attracts attention regardless of how useful or valid that particular cue may be. The research in NMCPL has indicated that validity and salience trade-off in predictable ways. Table 1 provides a summary of the main findings. People are good at learning which cues are valid for a given task and will utilize those cues accordingly. If all of the cues have the same validity then people will utilize cues with higher saliency. Increasing either a cue's validity or its saliency will enhance its utilization (to the detriment of other cues). Irrelevant cues also impact performance – adding an irrelevant cue decreases utilization of a valid cue, but the effect depends on the salience of the irrelevant cue – people must "notice" the irrelevant cue in order to utilize it and it takes a highly salient cue to attract attention to what is irrelevant (see Kruschke and Johansen 1999). People are also more adept at utilizing a single cue than using cues comprised of combinations or configurations of single cues.

The weather prediction task illustrated in Fig. 2 has been used extensively in studies of neurocognition, primarily to examine dissociations between declarative and procedural memory. The task putatively does not involve declarative memory because recalling previous trials should not help the learner avoid errors due to probabilistic feedback. Instead, the weather prediction task is presumed to rely on some implicit knowledge of the underlying probabilities associated with each cue combination. (In typical applications of the weather prediction task, on any given trial, any combination of present and absent cues may be shown to an observer; hence, cues occur not only in isolation but also in combination with other cues.) In support of this hypothesis, patients with amnesia were as successful as controls in learning the task (Knowlton et al. 1996). Because the weather prediction task (and MCPL generally) is concerned primarily with the aggregate cue utilization following learning, it is not clear to what extent differential strategy use plays a role in these studies. For instance, responses generated by always using a single cue can often result in similar performance to using a conjunction of cues (Gluck et al. 2002). Consequently, participants might follow a number of different strategies to arrive at the same level of aggregate performance making it difficult to infer what different levels of performance actually mean. Hence, it is difficult to assess the degree to which MCPL might rely on memory or implicit knowledge; however, recent analyses have aimed to determine the underlying strategy used in MCPL tasks and not just the level of accuracy.

Cross-References

► Behaviorism and Behaviorist Learning Theories
► Cognitive Tasks and Learning
► Complex Learning
► Design of Learning Environments
► Human Learning
► Neuropsychology of Learning

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t1.1 **Multiple-Cue Probability Learning. Table 1** Summary of important MCPL findings

t1.2	Increased validity leads to increased utilization
t1.3	Decreased validity leads to decreased utilization
t1.4	Increased salience leads to increased utilization
t1.5	Decreased salience leads to decreased utilization
t1.6	Validity and salience interact
t1.7	Increased utilization of one cue decreases utilization for other cues
t1.8	Salient but irrelevant cues decrease utilization of valid cues
t1.9	Single cues are easier to utilize than configurations of cues

		Feedback			
		Deterministic		**Probabilistic**	
	Outcomes →	**Discrete**	**Continuous**	**Discrete**	**Continuous**
Cues	**Discrete**	Categorization	Multiple Cue Judgment	NMCPL Multiple-Cue Learning Weather Prediction Task	Multiple Cue Judgment
	Continuous	Categorization	Function Learning	Metric MCPL	MCPL

Multiple-Cue Probability Learning. Fig. 1 Classification of concept-learning paradigms based on cues, outcomes, and feedback

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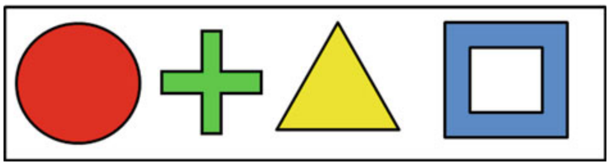

Probability of outcome X	
Circle	.45
Plus	.55
Triangle	.80
Square	.40

Multiple-Cue Probability Learning. Fig. 2 Example of an MCPL task