Reviewed by DOUGLAS CORIN

Book Review of Inferred Functions of Performance and Learning *by Siegfried Engelmann and Donald Steely*

In *Inferred Functions of Performance and Learning*, authors Engelmann and Steely aim to "identify what the intelligent system that produces responses must do to perform as it does" (p. vii). Included in the authors' theory is an explanation of how organisms learn. The theory has important implications for the design of formal instruction. "If a theory explains the variables involved in learning, an implication is that the control or maximization of particular variables would result in accelerated learning" (p. 489). This review focuses on several major aspects of the theory and the implications they hold for formal instruction.

Infrasystem and Agent

Every task imposes requirements on the task's performer, things that the performer must accomplish in order to perform the task. To refer to those things that must be accomplished, Engelmann and Steely use the term, *functions*. A function is any of a group of related actions that contributes to a larger action. The authors infer two classes of functions—those that can be performed reflexively in response to stimuli, and those that cannot. To adapt one of the examples presented by the authors—for a bee that knew that flying to red flowers would result in obtaining abundant nectar, certain actions would be performed reflexively. The bee would reflexively convert incoming physical stimuli (such as light) into corresponding internal sensory information, and it would reflexively screen for and recognize the color red as being a predictor of nectar. Other functions could not be performed reflexively because they depend on decisions based on information that varies from situation to situation. Before being able to obtain the nectar, the bee would need to take note of the present setting. It would need to find the distance and direction to the flower, and take into account any relevant features such as wind speed and obstacles. Not until it included this variable information in a plan of action, could the bee produce the behaviors necessary for obtaining the nectar in the present context.

The authors conclude, as the result of analyzing such tasks and behaviors, that organisms have a two-unit performance system. These two units are entities that are distinguished by their contributions to performance. The *infrasystem* is the reflexive unit of the performance system; it reflexively receives, screens, and enhances sensory input. The *agent* handles the situation-specific, consequence-governed functions needed for planning and producing behaviors.

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The agent does not operate reflexively, so it needs to be provided with motivation to perform. One major function of the infrasystem, therefore, is to influence the agent to actually produce the required plans and behaviors. The infrasystem reflexively enhances the incoming discriminative stimuli by creating and attaching secondary sensations (such as pain). The infrasystem then reflexively presents these enhanced sensations to the agent, motivating the agent to attend to the stimuli and to produce a relevant plan of action for the current setting. The agent responds to the infrasystem's enhancements by producing behaviors that increase the reception of positive sensations or that decrease the reception of negative sensations. The agent, therefore, produces operant behaviors. It makes plans, directs behaviors, and adjusts plans on the basis of sensory feedback via the infrasystem. All of these things require decisions by the agent, and so cannot be performed reflexively.

Content Maps

Another major aspect of the authors' theory is the implied existence of content maps. A content map is a type of blueprint that carries general information about an organism's goal in the present setting. For example, a general content map for a bee may be the equivalent of, "Fly to flowers to obtain nectar." The authors infer the existence of content maps by analyzing the behaviors of organisms and the logical requirements of tasks. A spider of a particular species may spin webs at various times and in various places, yet some of its behaviors or sequences of behaviors remain consistent across each web, implying that the spider is working from a general blueprint. All organisms need such general information prior to forming detailed plans of behavior, plans that must also take into account the specifics of the current situation. Without the information that is contained in content maps, the organism would not know what behavior to produce, or when to produce it. Therefore the infrasystem, in response to the presence of a discriminative stimulus, reflexively presents a content map to the agent. The agent is then able to apply the content map to the current situation by specifying the necessary details of behavior (e.g., for the bee, "Change direction to the north and fly lower.").

The essential foundation of all content maps is the information that allows an organism to predict a future event based on one or more features of the current situation. "If a flower is *red*, fly to it to obtain nectar" could be a more specific content map for a bee. The current red flower predicts future nectar. Apart from such predictions, the authors say, there is no basis for behavior. There is no motivation to respond to the stimulus.

Engelmann and Steely write that a complete content map specifies a purpose (e.g., "to obtain nectar"), a discriminative stimulus that informs the organism what to respond to (e.g., a red flower), and a response class (e.g., "fly"). For many organisms, the information in content maps may be hardwired. That hardwiring explains why some organisms can know how to produce unlearned behaviors—such as a spider knowing how to construct a web for the first time. For many of these same organisms, and for humans, certain content maps may be incomplete, or even nonexistent. This implies the need and the ability to learn. "Basic learning involves the completion of content maps" (p. 145). To form a complete content map, the learner must learn what predicts the reinforcer (e.g., "It is *red* flowers that predict nectar."), or what response strategy is called for (e.g., "fly, hover"), or both the predictor and the response strategy.

The Logical Processes Involved in Learning

One problem the learner may be faced with is that of identifying which features of the environment predict specific future outcomes. The authors use the example of a bee that is operating on a general content map such as, "Fly to flowers to secure nectar." In their example, the bee needs to learn the rule that abundant nectar is predicted only by flowers that include the single feature of being *red*. The authors label this a *single-feature predictor*, distinguished from *multiple-feature predictors* in which a combination of features (such as *tall and red*) are necessary to accurately predict a positive example.

The bee uses logical processes to learn the rule that *red* flowers predict nectar. The basic logical process used is that of comparison. When the bee lands on a flower that has nectar, the bee's infrasystem enhances all the recorded features of that flower. Those features would include the color red, as well as other features such as the flower's size, leaf shape, and stem height. After just one encounter with the positive (pollen-laden) flower, the bee has no logical basis for knowing which of the observed features predict nectar. Any single feature, or a combination of features, may be the predictor. Only by comparing features of the first flower with features of other encountered flowers, can the bee draw logical conclusions about which features predict pollen-rich, positive flowers. According to Engelmann and Steely, the basic logical conclusions are (a) any features shared by only positive flowers are retained as possible predictors, (b) any features held in common by a positive flower (one with nectar) and a negative flower (one without nectar) cannot be a predictor, and (c) any features found only in negative flowers cannot be predictors. According to the authors' bee example, there are two best possible sequences for encountering flowers, each sequence allowing the bee to identify the predictor by comparing just a single pair of examples. In one sequence, the next flower encountered is another positive flower that shares only one feature in common with the original positive (i.e., it is *red*), and all other features differ. Therefore, red is logically the only feature that can predict nectar. In the other sequence, the next flower encountered lacks nectar, but has exactly the same set of features as the positive flower except that it is *not red*. This minimum, single-feature difference between the nectar-rich flower and the flower without nectar logically rules out as a predictor every feature except red. Through such logical processes, the bee, and other organisms, are able to identify single-feature predictors.

Using similarly detailed examples, the authors also reveal the more complex logical processes needed to identify multiple-feature predictors, processes also based on comparison of features. The authors argue that these processes are necessary to all organisms, including humans, which learn and perform. The human system, however, "is able to learn more because it represents and retains more" (p. 347).

Implications for Formal Instruction

The theory of *Inferred Functions of Performance and Learning*, although broad enough to describe all learning, has specific implications for formal instruction. Engelmann and Steely carefully draw out the educational implications of the previously discussed aspects of their theory (i.e., content maps, the entities of infrasystem and agent, and the logic involved in learning).

Content maps are the key to performance of learned behavior. The process of learning is, essentially, the process of developing and elaborating content maps. By implication, the goal of formal instruction must be to induce these content maps. The authors explain that one way of inducing content maps is by using language. With language, the instructor can present the learner with a completed content map in the form of a verbal rule, circumventing the need for many trials of direct experience with concrete examples. The instructional designer can prepare rules that accurately predict the correct behavior across the full range of examples that the learner will encounter. Using language, the designer is able to focus the learner's attention on the relevant features of examples and help the learner avoid the distraction of irrelevant features. The conclusion is that learning can be greatly accelerated by inducing content maps verbally.

The authors provide general guidelines for teaching content maps through rules. "The learning of the rule involves three main steps: (a) saying the rule, (b) applying the rule to verbal examples, and (c) applying the rule to concrete examples. This order is radically different from that of traditional instruction" (p. 437). The authors provide some instances. A general content-map rule that the authors use for teaching children about fractions is, "The bottom number tells how many parts are in each group; the top number tells how many parts you use" (p. 444). Teachers and children then apply this rule to verbal examples and concrete examples. Through a sufficient range of examples, including fractions that equal one, those that are less than one, and those that are greater than one, children learn the generalization that the content-map rule applies to any fraction.

The theory of infrasystem and agent entities implies that instruction should also be designed for acceptance by the infrasystem. The infrasystem works with concrete examples from which it forms logical conclusions about predictive features. It also enhances those predictive features with secondary sensations so as to get the agent to attend to the features, and to motivate the agent to produce plans and responses. When verbal content-map rules are presented to a learner by the teacher, the predictive features of the map are not initially endorsed by the learner's infrasystem. The infrasystem endorses the rule only after experiencing sufficient examples of using the rule to obtain the results predicted by the rule. This implies the need for instructors to provide the learner with sufficient practice examples, so that the learner's infrasystem will endorse the rule as being a reliable predictor.

The authors' theory about the logic involved in learning has implications for designing teaching sequences, including those that use concrete examples. Such instruction should be designed to take advantage of the learner's inbuilt logical processes. To provide clear communication about features, the set of training examples should be designed to show the minimum difference between positives and negatives. This can best be achieved through using a contrived presentation that carefully sequences examples so that a change between one example and the next involves a change in only one feature. The system is then able to use the logic that, "If the change results in a negative example becoming positive, the change absolutely describes a feature that is essential to positive classification" (p. 247).

Throughout *Inferred Functions of Performance and Learning*, Engelmann and Steely have placed both performance and learning under a powerful microscope, a microscope consisting of the authors' detailed logical deductions and inferences. The result has been a highly magnified identification of the essential functions of performance and learning. For formal instruction, the overriding implication of their theory is that, "The learner's performance under uncontrolled presentations will never be as good as it would be under carefully controlled conditions" (p. 297). Through their analysis, the authors have revealed exactly which conditions to control, why to control them, and how.