

2 From Momentary Maximizing to
3 Serial Response Times and Artificial
4 Grammar Learning

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6 **Abstract**

7 Our overarching priority has been to develop method and theory to clarify the ideas of James and
8 Skinner on the importance of streams of thought and of behavior. We describe experimental
9 methods to quantitatively control and theoretical methods to explain the local continuity, or
10 moment-to-moment nature, of thought and behavior in time.

11 **Keywords:** optimality in behavior streams, optimality in categorizing, local-global attentional
12 switching, artificial grammar learning, local and global statistical learning in serial response times,
13 behaving theories

14 “The stream of thought” (James, 1890) emphasizes
15 that mental life is dynamic and continuously chang-
16 ing, and “the behavior stream” makes the same point
17 with regard to behavior (Schoenfeld & Farmer,
18 1970). These metaphors remind us of what seems
19 obvious but nevertheless is often neglected in con-
20 temporary behavioral science: Anything we do or
21 think comes after one thing and before something
22 else, and this local temporal patterning is usually
23 critical to understanding behavior. For example, the
24 order of words in a sentence changes the meaning of
25 an individual word, and the order of notes in a
26 melody changes the meaning of an individual note.
27 Individual words or notes may therefore carry little
28 meaning outside of the local patterning of words or
29 notes. We believe if scientific psychology is to under-
30 stand mental life and behavior, it must look to the
31 dynamic local temporal contexts of thoughts and
32 behaviors. An artificial hand or leg would be a poor
33 substitute for the real thing if it could not continu-
34 ously move, and method and theory for understand-
35 ing how a pitcher throws a baseball would do a poor
36 job if it applied only to a static, average hand posi-
37 tion. A snapshot of a person sitting in a chair, or

38 even a blurry composite image of a person walking
39 across a street might convey some useful informa-
40 tion but would scarcely tell us what it is like to
41 walk—that is, to actually behave. This point seems
42 so obvious that it says much about the enormous
43 power of tradition to shape scientific behavior when
44 we see many standard methods, concepts, and theo-
45 ries in behavioral science that scarcely acknowledge
46 it (Shimp, 1992, 2009). We are fascinated to observe
47 that even most theories of forgetting, attending, or
48 timing do not attempt to place these processes in
49 the context of continuous behavior streams. In
50 short, we believe there is great need to facilitate the
51 development of “behaving theories” that address the
52 continuity of behavior in time (Shimp, 1992, 2009).
53 As a result, in this chapter we have chosen to describe
54 what we believe is progress in developing some
55 newer experimental methods and “behaving theo-
56 ries” that explicitly address the local continuity, or
57 moment-to-moment nature, of behavior in time
58 (Shimp, 1992, 2009).

59 We have chosen to describe the stream of behav-
60 ior and the stream of thought by focusing on our
61 own comparative research. We have done so to make

1 the presentation more nearly manageable, but in
 2 doing so we regrettably have had to omit much
 3 essential work of others. Fortunately, much of this
 4 work appears elsewhere in this volume. We start by
 5 describing some of the intellectual priorities and
 6 themes that have guided our work.

7 An overarching priority has been to develop
 8 method and theory to clarify the ideas of James and
 9 Skinner on the importance of streams of thought
 10 and of behavior. James devoted an entire chapter in
 11 his classic *The Principles of Psychology* (1890) to the
 12 stream of thought, and Skinner spent much of his
 13 career closely examining local patterns of behavior
 14 in cumulative records. Skinner later lamented the
 15 extinction of cumulative records and their replace-
 16 ment primarily by overall properties of behavior.
 17 Looking only at overall average behavior is an emi-
 18 nently sensible activity if local properties of the
 19 stream that produce it are random. Otherwise, over-
 20 all output becomes problematic because the same
 21 overall output can obviously be caused by different
 22 interacting local processes. Local behaving seems
 23 scarcely ever to be random, so we have been moti-
 24 vated to study the local organization of behavior.

25 Three additional priorities have influenced much
 26 of our research. First, we have been enamored of
 27 discovering methods that actually control the quan-
 28 titative local performance of individual organisms,
 29 on the conventional scientific grounds that discover-
 30 ing variables that control something, in this case
 31 the stream of behavior, facilitates understanding it.
 32 Second, we have happily stolen method and theory
 33 from human cognitive psychology to study nonhu-
 34 man animal performances. Our approach has been
 35 to exploit human methodology when it has been
 36 shown to give insight into human cognition and to
 37 invoke the possibility of mental continuity when
 38 intuitively it has seemed that nonhuman analogous
 39 methods could be developed. Third, we have felt
 40 strongly the need for better theoretical understand-
 41 ing of the empirical literature on nonhuman animal
 42 performances. This in turn has led us to consider
 43 history, sociology, psychology, philosophy of sci-
 44 ence, and philosophy of language to gain perspec-
 45 tive on what it means to understand and evaluate a
 46 theory and has led us to search for implicit assump-
 47 tions and beliefs underlying claims on behalf of
 48 objective method and results (Benham & Shimp,
 49 2004; Shimp, 1990, 2001).

50 **Sequential Behaviors in Probabilistic Tasks**

51 When we began in the 1960s, probability learning
 52 was seen as a useful tool to study intelligence from a

comparative perspective and to facilitate the devel- 53
 opment of general theories of learning, such as stimu- 54
 lus sampling theory. The comparative question 55
 was a special case of how organisms behave ratio- 56
 nally or irrationally. As this chapter is being written, 57
 this question has recently arisen with some psycho- 58
 logical violence in the “everyday” financial world 59
 and in the more ethereal world of economic theory. 60
 In both cases, how humans deal rationally or irratio- 61
 nally with risk has apparently been widely misun- 62
 derstood. In the much smaller world of comparative 63
 cognition, the question is sometimes seen in terms 64
 of the relative intelligence of different species, and 65
 one can ask whether nonhuman animals probability 66
 match or maximize in probability learning tasks. 67
 That is, do they produce suboptimal steady-state 68
 choice probabilities that approximately equal or 69
 match corresponding reinforcement probabilities, 70
 or do they behave more rationally and tend exclu- 71
 sively to choose the alternative with the greater rein- 72
 forcement probability? In short, the comparative 73
 question when we began our research was whether 74
 nonhuman animals suboptimally “matched” or 75
 optimally “maximized.” This question is not of only 76
 esoteric laboratory interest, because behavioral eco- 77
 nomics sometimes looks for the evolutionary bases 78
 for human behavior, and accordingly, comparative 79
 laboratory studies of probabilistically reinforced 80
 choice behavior become potentially relevant to real- 81
 world human economic behavior. The comparative 82
 question was not the only reason why researchers 83
 were interested in this empirical question. Stimulus 84
 sampling theory was the best-articulated available 85
 quantitative theory of choice behavior, and it pre- 86
 dicted probability matching rather than max- 87
 imizing. For both comparative and learning-theory 88
 reasons, research therefore explored whether ani- 89
 mals matched or maximized. The answer turned out 90
 to depend on technical issues, including whether 91
 correction or noncorrection procedures were used 92
 (Shimp, 1966). While stimulus sampling theory 93
 sometimes used trial-by-trial sequential behavior 94
 to estimate theoretical parameters, most of the 95
 nonhuman animal empirical literature, being 96
 focused on overall choice as a measure of intelli- 97
 gence, did not, and researchers instead focused 98
 almost exclusively on overall choice proportions. 99
 In addition, researchers looked primarily at overall 100
 choice proportions because in a specific free-operant 101
 choice procedure (a particular kind of “concurrent 102
 variable interval schedule”), overall choice pro- 103
 portion matched overall reinforcement proportions 104
 (Herrnstein, 1961). 105

1 Our initial analysis of choice behavior examined
 2 both overall choice proportions *and* sequential
 3 properties of the behavior stream because sequential
 4 features of a behavior stream were important to the
 5 development of stimulus sampling theory. An early
 6 outcome of our research showed that pigeons tended
 7 locally to choose alternatives in a sequential manner
 8 that approximately maximized local reinforcement
 9 probability (“momentary maximizing”) in a way
 10 that seemed to explain the matching obtained by
 11 Herrnstein and others (Shimp, 1966). This demon-
 12 stration implied pigeons might generally learn local
 13 reinforcement probabilities in complex dynamic
 14 contexts, so we proceeded to examine more directly
 15 whether pigeons could discriminate local reinforce-
 16 ment probabilities that changed over time. We
 17 found that they could indeed discriminate among
 18 rapidly changing reinforcement probabilities for
 19 different choices, and we identified some task
 20 parameters that modulated the degree of precision
 21 with which they could do so (Shimp, Long, &
 22 Fremouw, 1996).

23 All these tasks were variations of probability
 24 learning tasks, and accordingly were of a discrete-
 25 trials type that could give only a sequence of static
 26 snapshots of the continuous behavior stream. We
 27 began to imagine how the behavior stream might
 28 consist of a succession of different behavioral units,
 29 each having some temporal extension, so that they
 30 themselves would involve temporal patterning.
 31 To explore this possibility, we made reinforcement
 32 contingent on extremely simple temporal patterns,
 33 interresponse times (IRTs), patterns consisting of an
 34 initial key peck followed by a prescribed temporal
 35 duration and terminated by a second key peck. We
 36 found that IRTs and even sequences of IRTs con-
 37 formed to lawful quantitative functions, and did so
 38 in ways that highlighted the crucial importance of
 39 temporal parameters of tasks, as would be expected
 40 from the perspective according to which the behav-
 41 ior stream consists of sequences of temporal patterns
 42 (Shimp, 1968). We then further generalized behav-
 43 ioral units to involve temporal durations between
 44 successive pecks on multiple keys (inter-changeover
 45 times) and found that they too depended lawfully
 46 not just on reinforcement probabilities but on the
 47 temporal durations as well (Shimp, 1979). These
 48 and other demonstrations (Hawkes & Shimp, 1975,
 49 1998) that complex local patterns of responding
 50 can be established and maintained by directly rein-
 51 forcing them led to the question of whether animals
 52 can actually remember the temporal order of their
 53 own behaviors. We therefore examined the simple

possibility that differential reinforcement estab- 54
 lished these complex patterns because an animal 55
 remembered having made them when a reinforcer 56
 was delivered. We asked if pigeons could remember 57
 the sequential order in which they had made recent 58
 responses and found that they could (Shimp, 59
 1976a). Other results described below on the rela- 60
 tion between implicit and explicit knowledge indi- 61
 cate that this result does not have universal 62
 applicability, but it suggests that at least on some 63
 occasions, there is a direct correlation between the 64
 local sequential organization of events a pigeon has 65
 recently encountered and how a pigeon “reports” or 66
 “describes” that serial organization. 67

We interpreted these results to imply that per- 68
 haps a great many different kinds of local temporal 69
 patterns of responding could be directly reinforced 70
 and shaped to function as higher-order units of 71
 behavior, the behaviors in terms of which phenom- 72
 ena, principles, and processes can be expressed. 73
 Serving as such units, these serial patterns of behav- 74
 ior would depend in elegant quantitative ways on 75
 their own temporal organization, as well as on rein- 76
 forcement parameters associated with them. Our 77
 results supported the speculation that at least some 78
 such local units consisted of behavioral patterns a 79
 subject could remember having made when a rein- 80
 forcer was delivered. We saw these results on local 81
 organization as generally compatible with a growing 82
 interest in the role of organization in human 83
 memory (Shimp, 1976b), and we saw them as 84
 encouraging mental continuity as a conceptual basis 85
 for the further exploration of the applicability of 86
 human method and theory to nonhuman animals. 87

Optimality in Categorization 88

Two features of the phenomenon of momentary 89
 maximizing attracted our special attention: local 90
 optimality and local serial organization. First let 91
 us consider optimality. It is easy to see optimality 92
 where there is none (Voltaire, 1959 [1759]). In our 93
 research, we have therefore tried to restrict our 94
 claims that performance was optimal to cases where 95
 optimal performance could be clearly defined and 96
 compared to nonoptimal performances. 97

Multidimensional Categorization 98

Multidimensional categorization can be conceptu- 99
 alized as a generalization of choosing between avail- 100
 able alternatives such as left or right, or red, yellow, 101
 or green, in a probability learning task. Accordingly, 102
 categorization tasks can investigate the degree 103
 to which nonhuman animals choose optimally. 104

1 The literature on complex, multidimensional cate- 33
 2 gorization in humans grew exponentially when cate- 34
 3 gories ceased to be viewed primarily in terms of the 35
 4 binary logic of truth tables and began to be viewed 36
 5 in more naturalistic ways involving natural language 37
 6 and permitting some ambiguity in the definitions of 38
 7 categories. We see a parallel transition between early 39
 8 and late philosophies of Wittgenstein (1922, 1953). 40
 9 A procedure that has proven useful to the study of 41
 10 optimality in multidimensional categorization is the 42
 11 randomization procedure (Ashby & Maddox, 43
 12 1998). In this procedure, a two-dimensional cate- 44
 13 gory is represented as a bivariate normal distribu- 45
 14 tion. Such distributions are well suited to research 46
 15 on categorization because potentially limitless num- 47
 16 bers of individual exemplars can be sampled from 48
 17 them, matching the limitless exemplars that consti- 49
 18 tute real-world categories such as “tree,” “pigeon,” 50
 19 or “rock.” Prototypical exemplars are located toward 51
 20 the peak of the distribution, and are thus more 52
 21 likely to be sampled. Atypical exemplars are located 53
 22 further away, and are less likely to be sampled. 54
 23 Figure 34.1 is taken from Herbranson et al. (1999) 55
 24 and summarizes the procedure. The left panel 56
 25 depicts two category distributions, A and B. The 57
 26 space over which the distributions are defined is 58
 27 typically referred to as the stimulus space, in which 59
 28 each point represents a particular two-dimensional 60
 29 stimulus (for example, a rectangle with width x and 61
 30 height y). The third coordinate, z , is the likelihood 62
 31 with which that stimulus will occur given a particu- 63
 32 lar category. The right panel in Figure 34.1 shows

two equal-likelihood contours, each of which effi- 33
 ciently summarizes a bivariate normal distribution 34
 by showing points corresponding to stimuli that are 35
 equally likely to occur given a particular category. 36
 The right panel also shows the optimal decision 37
 bound, the line formed by the points corresponding 38
 to stimuli that are equally likely to occur given either 39
 category. Optimality of responding is easily diag- 40
 nosed with this procedure because a participant 41
 maximizes the likelihood of correct categorization if 42
 stimuli on one side of the optimal decision bound 43
 are categorized as belonging to Category A and 44
 stimuli on the other side are categorized as belong- 45
 ing to Category B. 46

As it has been our custom to explore mental conti- 47
 nuity, we adapted this procedure for use with non- 48
 human animals. We showed pigeons rectangles of 49
 varying lengths and widths. After a rectangle was 50
 presented, a bird could categorize the rectangle by 51
 pecking one of two locations, each of which corre- 52
 sponded to one of the two categories, A or B. If a 53
 response corresponded to the category from which 54
 the presented stimulus had been drawn, a bird was 55
 presented with food. Across conditions, we sampled 56
 stimuli from categories that yielded different opti- 57
 mal decision bounds (corresponding, for example, 58
 to rules such as “go left if a rectangle is wider than 59
 tall; otherwise, go right,” or “go left if a rectangle is 60
 wider than the average width regardless of its 61
 height”). In each condition, the great majority of 62
 pigeons’ categorizations were optimal, with averages 63
 ranging from around 77% to 91%, depending on 64

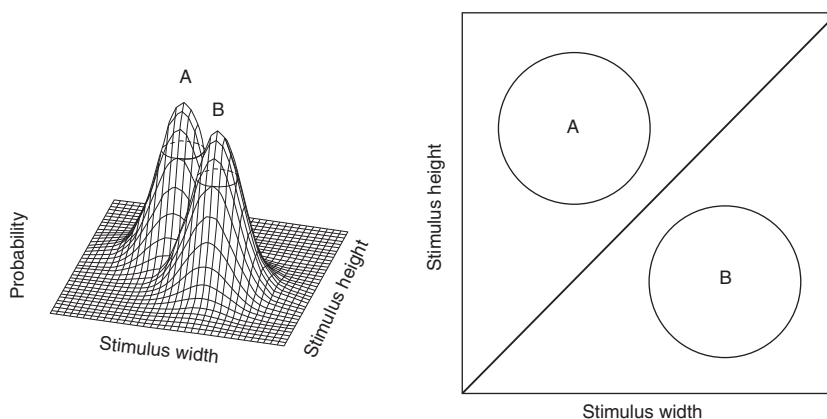


Fig. 34.1 *Left panel:* Bivariate normal distributions representing the likelihoods with which specific rectangles could be sampled from either of two overlapping categories, A and B. Each point in the stimulus space corresponded to a rectangle having a width and height equal to the x and y coordinates, respectively. One arbitrary contour of equal likelihood is shown for each category. Each contour consisted of all points corresponding to rectangles equally likely to be sampled from the distribution. *Right panel:* Arbitrary contours of equal likelihood for each category and the corresponding linear optimal decision bound (from Herbranson, Fremouw, & Shimp, 1999).

1 the specific categories used. Furthermore, we found
 2 that if accurate categorization in a condition
 3 required information from both stimulus dimen-
 4 sions, pigeons generally divided attention between
 5 the two dimensions and made choices that were
 6 roughly optimal. Similarly, if categories were defined
 7 based on a single dimension (with the second stim-
 8 ulus dimension varying randomly), pigeons selec-
 9 tively attended to the relevant dimension and again
 10 made choices that were roughly optimal. These
 11 results mirrored those that have been obtained from
 12 human participants in similar situations (Ashby &
 13 Maddox, 1998). Note that the stimuli used in these
 14 categorization tasks, indeed in virtually all categori-
 15 zation tasks, with humans as well as nonhuman
 16 animal subjects, are static, whereas naturalistic stim-
 17 uli are often dynamic. We accordingly adapted
 18 the categorization task so that the two dimensions
 19 were the speed and direction with which a virtual
 20 object moved across a computer screen (Herbranson,
 21 Fremouw, & Shimp, 2002). We surmised that
 22 pigeons might perform well on this task because in
 23 their natural environment, the ability to categorize
 24 some moving objects (say, predators) in terms of
 25 their dynamic characteristics could be quite useful.
 26 We did in fact discover that pigeons used speed and
 27 direction to categorize moving objects with aston-
 28 ishing precision and, on the average, with almost
 29 perfect optimality (Fig. 34.2). We believe this opti-
 30 mal categorization of an object moving on different

31 trials at different speeds and in different directions
 32 greatly generalizes our original phenomenon of
 33 momentary maximizing. Pigeons can learn how
 34 local reinforcement probability rapidly changes as a
 35 function of several different kinds of local environ-
 36 mental stimuli, including stimuli in tasks involving
 37 different kinds of static and dynamic multidimen-
 38 sional stimuli, features of their own behavior, and
 39 patterns of recent events.

40 We think these highly diverse forms of locally
 41 controlled behaviors suggest that nonhuman animals
 42 accurately estimate local reinforcement probabilities
 43 and temporal task parameters within the context of a
 44 behavior stream, and can do so with a level of preci-
 45 sion that is generally underestimated. Our results
 46 suggest that it is especially underestimated when
 47 conventional empirical procedures do not permit a
 48 researcher to directly estimate local control so that
 49 the possibility is ignored altogether (Shimp, 1973,
 50 1979). We think a more careful approach, given the
 51 range of precise local control that can be demon-
 52 strated, is to explicitly show local control does not
 53 apply before assuming that it does not.

Attentional Dynamics

54 A stream of mental life may quickly change course if
 55 an organism encounters an hierarchically structured
 56 stimulus like a forest and its component trees, to
 57 which one can attend in either a global or a local
 58 manner. The ability to quickly switch between
 59

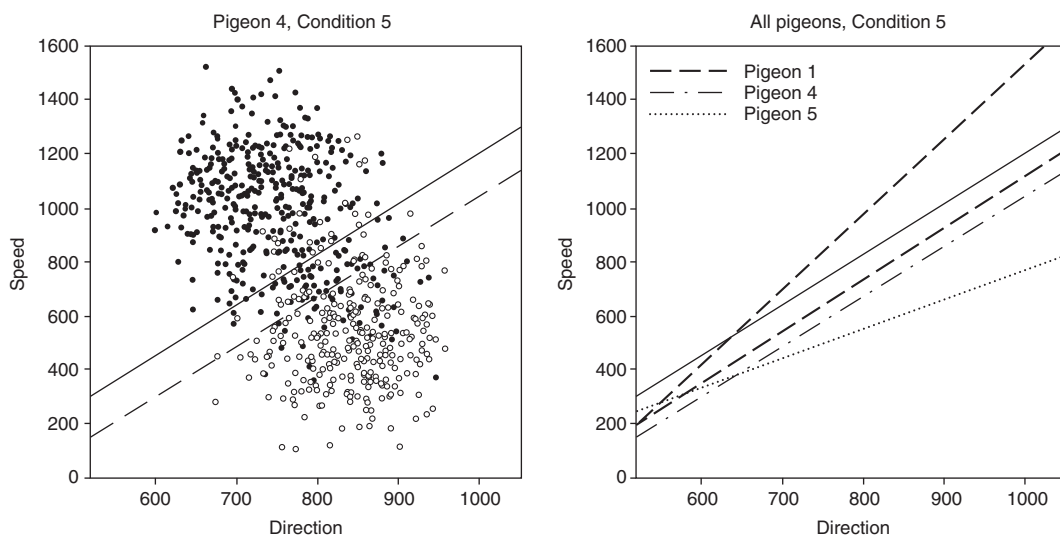


Fig. 34.2 *Left panel:* The obtained stimulus space for one bird in Herbranson, Fremouw, and Shimp (2002). Filled and open circles correspond to individual responses categorizing stimuli as members of categories A and B, respectively. The dashed line shows the estimated decision bound for this bird, and the solid line shows the optimal decision bound. *Right panel:* Individual estimated decision bounds for three birds, along with average estimated (bold dashed) and optimal (bold solid) decision bounds.

1 global or local analyses, as in attending either to a
 2 forest or its trees, is important if, as often seems to be
 3 the case, reinforcement depends on the level of the
 4 stimulus. Humans can, of course, switch back and
 5 forth between these levels of perceptual analysis, and
 6 this ability permits humans to respond over short
 7 periods of time in more nearly optimal ways. We
 8 have used hierarchically organized stimuli to show
 9 that pigeons, much like humans, can shift attention
 10 either to local or global features of stimuli.

11 We presented pigeons with complex stimuli
 12 having both a global and a local level (Navon, 1977).
 13 Pigeons were “primed” at either the local or global
 14 level, and rewarded for responding to targets that
 15 could occur at either level. On each trial, pigeons
 16 were shown an hierarchical stimulus (i.e., a global
 17 character that was created from a number of smaller,
 18 local characters). For each set of hierarchical stimuli
 19 there were two possible target stimuli and two possible
 20 irrelevant “distractor” stimuli. Both the target
 21 stimuli and the distractor stimuli could occur at
 22 either the local or the global level, resulting in a
 23 total of eight hierarchical stimuli, four with a target
 24 stimulus at the global level and a distractor stimulus
 25 at the local level and four with a target stimulus at
 26 the local level and a distractor stimulus at the global
 27 level. One such hierarchical stimulus set is shown in
 28 Figure 34.3. Pigeons were rewarded for pecking the
 29 left key if one target was present in the hierarchical
 30 stimulus and the right key if the other target was
 31 present in the hierarchical stimulus, regardless of
 32 the level at which that target occurred. In short, the
 33 pigeon had to search for a target that could be present
 34 at either the local or global level.

Initially, we asked if pigeons could change the
 level to which they attended based on the frequencies
 with which targets at different levels occurred. That is,
 we used a base-rate procedure to train (prime) the
 pigeons to expect a target at a particular level (Fremouw,
 Herbranson, & Shimp, 1998). Specifically, we presented
 successive blocks of trials within which targets at the
 primed level occurred 85% of the time and the targets
 at the non-primed level occurred the remaining 15% of
 the time. Over the course of the experiment we alternated
 blocks of trials with either global or local levels primed.
 The notion of mental continuity led us to believe that
 pigeons, like humans, would respond faster to targets
 at the primed level than to the same targets at the
 non-primed level. That is what we found. Response
 times were significantly faster to local targets than to
 global targets during the blocks in which targets
 appeared more frequently at the local level (local level
 primed), and response times were significantly faster to
 global targets than to local targets during the blocks
 in which targets appeared more frequently at the global
 level (global level primed). These results suggest that
 pigeons can flexibly switch attention between local and
 global levels of perceptual analysis.

These first experiments did not identify the time frame
 over which pigeons can switch attention. Attention might
 have built up slowly as the base rates were learned,
 and once built up at the primed level, it might have
 simply remained “active” at that level until the base
 rate changed. However, we believed that in nonhuman
 animals, as is the case in humans, shifts of local–global
 attention can occur

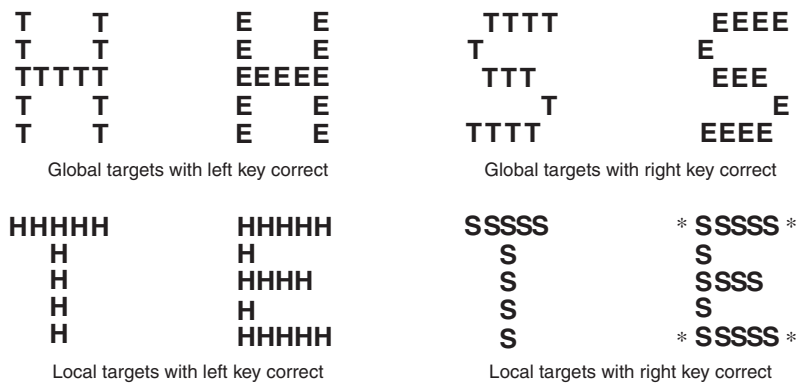


Fig. 34.3 Stimuli similar to those used by Fremouw et al. (1998, 2002). Each hierarchical stimulus had a target stimulus (here either an H or an S) at either the local or global level and an irrelevant distractor stimulus (here either an E or a T) at the other level. The four stars used as a prime in the trial-by-trial priming version of the task (Fremouw et al., 2002), are shown surrounding the bottom right hierarchical stimulus. The stars were presented 1 second or less before a hierarchical stimulus was presented and the color of the stars (red or green) primed a pigeon to the perceptual level at which the target was more likely to occur.

1 much more quickly. In accordance with our intuitive notions about the stream of consciousness, we believed that moment-to-moment experiences often drive moment-to-moment dynamic shifts in attention. To explore this notion in the case of local–global attention we ran a series of new experiments in which we used a trial-by-trial cuing procedure to train (prime) the pigeons to expect a target at a particular level (Fremouw, Herbranson, & Shimp, 2002). On each trial, we presented a brief priming cue a second or less prior to the presentation of the hierarchical stimulus. In one of the experiments the priming cue consisted of four stars, either all green or all red, that formed the corners of a box slightly larger than the stimuli. The color of the stars predicted, with 85% accuracy, the level at which the target would occur. Targets occurred at the global level a random 85% of the time and at the local level the other 15% of the time if the stars were red (a global prime), and vice versa if the stars were green (a local prime). Local and global targets occurred with equal probabilities overall. As was the case for the base-rate priming, trial-by-trial priming caused a significant change in response time, suggesting that pigeons can flexibly switch attention between local and global levels of analysis, in this case on a moment-to-moment time frame, comfortably compatible with the metaphor of a continuous stream of mental life.

20 We see the outcomes of these experiments on shifts between local and global levels of attention as entirely compatible with our previous work on shifts between spatial attention to one location or another (Shimp & Friedrich, 1993): in both cases, pigeons can flexibly and quickly switch attention. We accordingly think, again simply because of the possibility of mental continuity, that it is reasonable to anticipate a dynamic attention system across many species. In this we are guided especially by Gestalt ideas that imply the possibility that the stream of mental life can involve rapid switches between local and global levels of analysis as examples of reversals between figure and ground. We believe that these demonstrations of dynamic shifts of attention in nonhuman animals suggest that local dynamics shape to some degree, as it does in humans, what animals see at any moment. That is, we agree with the cognitive position according to which dynamic attentional shifts rapidly change representations of stimuli in streams of thinking. We accordingly believe that long-term theoretical goals will have to include explaining both these rapid shifts of attention and their effects on streams of thinking and of

54 behaving. We believe the importance of these goals is generally underestimated when analyses focus exclusively on long-term average performance.

57 We think it is sufficiently important to ponder potential mechanisms for attentional shifts to warrant noting that recent neurophysiological findings from bats offer some intriguing possibilities for how feedback between cortex and lower sensory nuclei might play a role in attentional phenomena on both slower time scales, such as in the blocking task, and on faster time scales, such as in the cuing task. Suga et al. (Ma & Suga, 2003; Suga, Gao, Zhang, Ma, & Olsen, 2000) showed that repetitive stimulation of auditory cortex can refine and strengthen neuronal firing in the inferior colliculus, a nucleus that occurs earlier in the auditory processing stream than auditory cortex. For example, stimulating an area of cortex that responds best to a particular frequency range or to a particular delay between sounds seems to strengthen the response of neurons in the inferior colliculus that also respond to that particular frequency range or delay. Inactivation had the opposite effect: The response in the inferior colliculus weakened. This neuronal modulation developed over time, from 2 to 30 minutes, and lasted from minutes to hours. Casseday, Fremouw, and Covey (2002) speculated that this process might help select, enhance, and maintain processing of specific auditory features over the time course of a bat's evening hunt.

84 We wonder if a similar mechanism, perhaps working on spatial frequency, might play a role in creating local–global attention seen in the base-rate blocking experiments where the dynamics of attention may be relatively slow. Perhaps the high base rate of a particular target level leads to repetitive and prolonged activity of neurons tuned to the appropriate spatial frequency for the corresponding perceptual level. Perhaps once a target level is perceived on a trial, the neurons involved in encoding that level remain active longer, and at a higher level than the neurons that encode the non-target level. Such increased activity might then strengthen and fine-tune the response of neurons to that level in both visual cortex and earlier structures. The enhanced neuronal response might in turn produce faster or more accurate perception of subsequent targets at that perceptual level.

102 Activity in auditory cortex can also enhance specific auditory features in the inferior colliculus on a much faster, stimulus-by-stimulus time frame (Jen, Chen, & Sun, 1998; Zhou & Jen, 2000). Perhaps a similarly fast-acting mechanism plays a role in the

1 visual system and at least partially mediates the
 2 local–global attention shifts seen in the priming cue
 3 task. We describe these speculative possibilities to
 4 illustrate how research on neurophysiology might
 5 inform understanding of continuous behavior
 6 streams and streams of mental life, and vice versa.

7 In summary, we showed that pigeons display
 8 flexibility in switching attention between local and
 9 global levels of perceptual analysis in a manner sim-
 10 ilar to that of humans attending either to the forest
 11 or the trees. Thus, pigeons can flexibly display a
 12 kind of rapid figure–ground reversal that forms part
 13 of the core meta-theoretical perspective of Gestalt
 14 psychology.

15 **Artificial Grammar Learning**

16 As we conducted pigeon experiments on the effects
 17 of local context on such diverse phenomena as opti-
 18 mality in choice behavior, the behavior stream,
 19 local–global attentional switching, spatial attention,
 20 and multidimensional category learning, (as well as
 21 on serial response times as we describe in the next
 22 section), and found in each case that local context
 23 had profound effects on behavior, we began to spec-
 24 ulate on the possibility that pigeons might be sensi-
 25 tive to local context even in the form of grammatical
 26 context. Grammar has been identified as one of the
 27 key issues in the “cognitive revolution” (Gardner,
 28 1985). Chomsky’s (1959) attack on Skinner’s (1957)
 29 analysis of verbal behavior was largely focused on
 30 the linear chaining that seemed implicit in Skinner’s
 31 analysis and that became explicit in the “Jack and
 32 Jill” demonstrations of two pigeons communicating
 33 (Epstein, Lanza, & Skinner, 1980). The role of
 34 grammar was prominent by its virtual absence in
 35 Skinner’s analysis of language. While Chomsky’s
 36 attack may have been more relevant to 1930s meth-
 37 odological behaviorism and to the reductionism
 38 inherent in logical positivism than to Skinnerian
 39 radical behaviorism, Chomsky certainly assigned to
 40 grammar a far greater role in language than Skinner
 41 did. We knew that the problem of animal “lan-
 42 guage” was controversial but felt we could approach
 43 it from a new and constructive perspective by using
 44 Artificial Grammar Learning (AGL), a method that
 45 Chomsky and Miller (1958) had described years
 46 earlier, and that Reber (1967) had used to excellent
 47 purpose in the study of implicit versus explicit
 48 knowledge in humans. AGL research continues to
 49 be actively pursued with human participants and is
 50 informing our understanding of the evolution of
 51 component mechanisms of natural language, if not
 52 directly of natural language itself. AGL seemed to us

53 to offer a potentially powerful tool for examining
 54 how local context affects visual categorization,
 55 specifically how pigeons categorize letter strings
 56 generated by formal rules. We saw AGL as a way to
 57 move our comparative work on local sequential
 58 structure toward increasingly complex stimuli. We
 59 hoped that sharply focusing on whether pigeons
 60 could learn artificial grammars would facilitate clar-
 61 ifying mechanisms that might be involved in lan-
 62 guage while letting us avoid some of the more
 63 intangible and inscrutable problems that would
 64 arise if we asked generally if pigeons could learn
 65 language (for discussion, see Savage-Rumbaugh,
 66 Shanker, & Taylor, 1998; Rumbaugh & Washburn,
 67 2003; and Terrace, 1979).

68 An artificial grammar (Reber, 1967) is a set of
 69 rules for generating strings of characters. An exam-
 70 ple of one such grammar is depicted in Figure 34.4.
 71 A character string is generated by entering the gram-
 72 mar at the left, with each transition from one state
 73 to another adding a character to the string, until
 74 exiting via the “out” arrow at the right. In this
 75 manner, each unique path through the grammar
 76 produces a different character string. By virtue of its
 77 recursive loops, the grammar shown can generate an
 78 infinite number of unique character strings. Limiting
 79 the length of character strings naturally decreases
 80 this number, but still results in a large number of
 81 unique strings. The simple grammar depicted in
 82 Figure 34.4, for instance, can generate 43 character
 83 strings between three and eight characters in length.
 84 Note that local sequential context is critical to the
 85 grammar’s definition, in the sense that grammatical-
 86 ity is not determined by individual letters or total
 87 numbers of letters, but by the sequential order in
 88 which letters appear.

89 In a prototypical artificial grammar experiment
 90 such as that of Reber (1967), undergraduates were

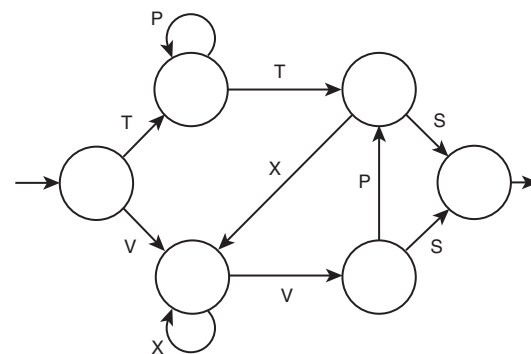


Fig. 34.4 The artificial grammar used by Reber (1967) and by Herbranson and Shimp (2003, 2008).

1 shown grammatical character strings and asked to
 2 memorize them. Later, they were presented with
 3 novel strings and were told the letter strings they
 4 had memorized earlier were generated by a gram-
 5 mar. They were not, however, shown the grammar
 6 or told anything about it. They were simply asked
 7 whether the novel strings conformed to the same
 8 grammar. Despite the participants' inability to accu-
 9 rately describe the rules of the grammar, perfor-
 10 mance at diagnosing grammaticality was reliably
 11 above chance. This result parallels an important
 12 aspect of normal language acquisition in young
 13 children, who recognize grammatical sentences
 14 when they hear them, and do so without being able
 15 to describe grammatical rules. It also parallels the
 16 learning of naturalistic visual categories where cate-
 17 gories such as "tree" are quickly learned, even though
 18 the basis for the discrimination may be unclear even
 19 to the experimenter himself, let alone to the accu-
 20 rate categorizer. From the perspective of the partic-
 21 ipants, artificial grammars have the virtue of
 22 preserving the "family resemblance" characteristic
 23 of naturalistic categories, where the basis for the
 24 discrimination seems complex and ambiguous
 25 (Wittgenstein, 1953). At the same time, from the
 26 perspective of the experimenter, artificial grammars
 27 have the virtues of simplicity and precision: The
 28 experimenter actually knows the rules, the true
 29 structure, of the category (which is not the case with
 30 most naturalistic categories, such as "tree").

31 Artificial grammar learning in humans may
 32 involve nonlinguistic precursors of component pro-
 33 cesses of human language and therefore deserves a
 34 comparative analysis (see Gebhart, Newport, & Aslin,
 35 2009; Gentner, Fenn, Margoliash, & Nussbaum,
 36 2006; Seidenberg, MacDonald, & Saffran, 2002; and
 37 Zeigler & Marler, 2008, for related discussion).
 38 Pigeons can learn an artificial grammar (Herbranson
 39 & Shimp, 2003). We trained birds to discriminate
 40 between grammatical and nongrammatical charac-
 41 ter strings. Birds were rewarded for pecking one key
 42 when a character string was displayed that con-
 43 formed to the rules of the grammar in Figure 34.4.
 44 They were rewarded for pecking a different key
 45 when the displayed character string violated the
 46 grammar. After extensive training (mean of 179
 47 days of training), birds reached a stable level of
 48 above-chance performance (62.3% correct) on the
 49 training set of 62 character strings (31 grammatical
 50 and 31 nongrammatical), suggesting that they
 51 may have learned something about the grammar,
 52 or at least had learned something correlated with
 53 some of the rules of the grammar. To examine the

54 possibility that pigeons were simply memorizing
 55 specific training exemplars, at least some of which
 56 presumably seemed familiar to the pigeons by the
 57 end of training, we subsequently presented novel
 58 probe strings (12 novel grammatical and 12 novel
 59 nongrammatical strings) that the pigeons had not
 60 encountered during training. Performance on these
 61 novel strings was also reliably above chance (60.7%),
 62 supporting the notion that pigeons acquired a flex-
 63 ible conception of the grammar that went beyond
 64 the specific stimuli presented during training.

65 Most important for our purposes here is that the
 66 grammatical status of a character string depended
 67 on its local spatial organization. This spatial organi-
 68 zation was linear, and in that sense spatially sequen-
 69 tial, but of course a pigeon did not necessarily
 70 process the linear string in a corresponding sequen-
 71 tial order. (An interesting question for future
 72 research would be whether a pigeon can be trained
 73 to process character strings in a particular sequential
 74 order, and if so, whether the order of processing
 75 affects judgments of grammaticality depending on
 76 the information serially provided by different
 77 sequences.) Both grammatical and nongrammatical
 78 strings consisted of the same component characters,
 79 and the only difference that allowed a pigeon to
 80 accurately discriminate between them was the local
 81 sequential organization of the characters. We specu-
 82 late that a striking asymmetry in the data of this
 83 experiment further supports the importance of
 84 sequential organization. Pigeons' categorizations of
 85 grammatical character strings were reliably above
 86 chance (70.0% correct), while their categorizations
 87 of nongrammatical character strings were not
 88 (51.4% correct). We interpret this asymmetry as
 89 having been caused by grammatical strings having
 90 consistent local sequential organization that non-
 91 grammatical strings lacked.

92 This first AGL experiment motivated us to con-
 93 duct a second set of experiments (Herbranson &
 94 Shimp, 2008) designed to clarify the role of local
 95 sequential organization. One experiment used the
 96 same general procedure outlined above, but rather
 97 than discriminating between grammatical and non-
 98 grammatical character strings, pigeons were required
 99 to discriminate between two sets of grammatical
 100 character strings generated by two different gram-
 101 mars. That is, both categories of character strings
 102 derived from consistent rules, and as a result, the
 103 asymmetry in performance was eliminated: Pigeons
 104 learned both categories with performance above
 105 chance for each (78% and 75%). Learning was also
 106 much faster than in the first AGL experiment, so

1 much faster than in fact the learning rate was well
 2 within those of many visual discrimination tasks.
 3 Some investigators find rapid learning rate to be an
 4 important criterion for identifying “natural” cogni-
 5 tive processes, and our first AGL experiment may
 6 have left some researchers wondering how general
 7 our results could have been. The second experiment
 8 left little doubt, we believe, that by the standards of
 9 plain English, pigeons can learn sequential rules
 10 that generate large numbers of character strings.

11 We believe these AGL experiments importantly
 12 extend what is known about what at least some
 13 nonhuman animals can learn about arbitrary,
 14 abstract, sequential rules. The artificial grammars in
 15 these experiments were indeed artificial; the rules
 16 were abstract relations involving sequential order of
 17 arbitrary characters. If food reward is sufficient to
 18 teach pigeons such arbitrary, “meaningless,” sequen-
 19 tial relations, we think it becomes all the more likely
 20 pigeons can and do learn sequential relations in
 21 other contexts where, because no sequential rela-
 22 tions are *required* for reinforcement, it may be incor-
 23 rectly assumed that no learning of sequential context
 24 takes place (Shimp, 1976b). That is, we speculate
 25 that the metaphors of behavior streams and streams
 26 of mental life should be the default interpretations:
 27 Attention to, and control by, local structure should
 28 be assumed unless otherwise shown to be irrelevant
 29 to performance. This suggestion is equivalent to
 30 suggesting that a Gestalt-like interpretation be care-
 31 fully examined before automatically adopting a
 32 more atomistic, reductionistic interpretation or
 33 one involving only long-term average performances.
 34 In the specific case of language, we thereby ally
 35 ourselves with Chomsky and others who emphasize
 36 the role of sequential structure. Finally, we think
 37 it is important that our experiments, especially our
 38 second set of experiments, show that pigeons can
 39 learn relatively complex sequential structure rapidly,
 40 without the kind of social interaction that has been
 41 part of other demonstrations of complex sequential
 42 patterns in avians (Pepperberg, 2000) and without
 43 the kind of conceptual processing that may be
 44 involved in the case of perception of musical or
 45 artistic style (e.g., Porter & Neuringer, 1984;
 46 Watanabe, Sakamoto, & Wakita, 1995).

47 **Local Temporal Context:**
 48 **Serial Response Times**

49 It would not surprise us if it turned out that AGL
 50 could be interpreted in terms of statistical learning
 51 processes—that is, of mechanisms that learned the
 52 statistical likelihoods of various categories, includ-

ing ill-defined categories, of complex sequences. 53
 That is, we suspect that probability learning and the 54
 kind of quantitative rule learning that develops in 55
 the randomization task may turn out to also iden- 56
 tify processes responsible for learning sequential 57
 dependencies in AGL. Recent evidence already 58
 indicates, for example, that human infants quickly 59
 learn statistical relations in natural language 60
 (Gebhart, Newport, & Aslin, 2009; Safran, 2003). 61
 We do not claim that statistical learning mecha- 62
 nisms acting independently could explain natural 63
 language, but they might provide essential input to 64
 a larger set of dynamically interacting mechanisms 65
 that could do so. 66

67 We have developed a response time task that is
 68 uncovering statistical learning mechanisms that may
 69 have contributed to the evolution of language and
 70 may still play a role in language learning in humans.
 71 Response times have generally had a bad reputation
 72 in behavior analysis (but with noteworthy excep-
 73 tions; see Blough, 2006) and a good one in cogni-
 74 tive psychology. Skinner derided response times
 75 because they had formed a key component of
 76 mentalism since the earliest days of experimental
 77 psychology, and they involved discrete-trials meth-
 78 odology rather than the continuous free-operant
 79 methodology he advocated. Nevertheless, we began
 80 to use them because these complaints seemed more
 81 philosophical or meta-theoretical than empirical.
 82 Furthermore, from the perspective of ebb and flow
 83 in streams, a response time of as little as several
 84 hundred milliseconds might involve considerable
 85 mental dynamics and causal processing, and from
 86 our mental-continuity perspective, being allied to
 87 human cognitive psychology is as much a virtue as
 88 it is a problem.

89 We became interested in a serial response time
 90 task that is very familiar in human neuropsychology
 91 but is less so in comparative cognition and still less
 92 so in behavior analysis. The procedure turns out to
 93 be an astonishingly easy task for pigeons to learn so
 94 that it permits the efficient study of effects of local
 95 temporal and statistical information. We have been
 96 further impressed by the elegance of the data it has
 97 produced and by the parsimonious theoretical inter-
 98 pretation to which the data submit.

99 Froehlich, Herbranson, Loper, Wood, and Shimp
 100 (2004) developed a serial response time procedure
 101 patterned after a classic human-participant proce-
 102 dure of Nissen and Bullemer (1987) (also see
 103 Vickrey & Neuringer, 2000). We required a pigeon
 104 to peck sequences of target keys successively lit
 105 across three spatial locations. In some versions of

1 the task, the sequentially lit locations were random,
 2 and in others, they followed a repeating list, such as
 3 LRCCLRLRC. . ., where L, C, and R stand for left,
 4 center, and right locations, with the nine-item list
 5 starting over at the beginning after the terminal C.
 6 Response times were measured from the onset of a
 7 lit key until a pigeon pecked it. The task permitted
 8 recording several hundred response times from each
 9 pigeon in each day's session because pecks were rein-
 10 forced only intermittently. The question was what a
 11 pigeon learned about the sequential structure of the
 12 list. We answered it in terms of the first-order and
 13 second-order local likelihoods with which one spa-
 14 tial location followed another. We computed the
 15 first-order local likelihood as shown in the following
 16 example. The first-order local likelihood that C
 17 followed R in the above list was $2/3$ (the third
 18 and ninth items in the list involved center-lit keys
 19 following right-lit keys) and there was one occasion
 20 on which R was not followed by C (it was followed
 21 by L), so two of three occasions of C followed R.
 22 Second-order local likelihoods of a spatial location
 23 given the previous two locations were computed
 24 similarly. For instance, in the same list, LRCCLRLRC,
 25 the second-order local likelihood of R, given a pre-
 26 vious C and L, was $2/2$. We described what a pigeon
 27 knew about the first-order and second-order struc-
 28 ture of a list by plotting response time as a function
 29 of the first- and second-order local likelihoods com-
 30 puted in this manner. Over experimental condi-
 31 tions, we varied the sequential structures of the
 32 nine-item lists, the intertrial interval, and the base
 33 rate of occurrences of the three different locations
 34 within a list.

35 Pigeons rapidly learned the first- and second-or-
 36 der local likelihoods with which one location fol-
 37 lowed a previous one or two locations, in the sense
 38 that response time, averaged over several pigeons,
 39 decreased in accordance with a straight line as the
 40 likelihood of a location increased; the more likely a
 41 location, the faster a pigeon responded to it. We
 42 interpreted this function to show how a pigeon used
 43 local statistical information to "anticipate" the next
 44 location. We found that the slope of the function
 45 relating response time to local information was sim-
 46 ilar to that obtained with human participants. In a
 47 second experiment, we varied intertrial interval and
 48 found that the optimal intertrial interval was
 49 approximately the same as with human participants.
 50 In a third experiment, we varied the global likeli-
 51 hood with which a spatial location appeared within
 52 random conditions in which the location of one
 53 item provided no local sequential information about

54 the location of the next item. We expected some
 55 degree of rational use of overall base-rate informa-
 56 tion: we expected that a pigeon in an unstructured
 57 condition with unequal base rates would respond
 58 more quickly to a spatial location that occurred
 59 more frequently than another. Instead, we found a
 60 not uncommon phenomenon in the human litera-
 61 ture, base-rate neglect, a form of irrational and less-
 62 than-optimal behavior in the sense that overall
 63 statistical information was not used (Tversky &
 64 Kahneman, 1990). Thus, we found on the one hand
 65 in the first experiment that local statistical informa-
 66 tion was learned and used, and on the other hand,
 67 in the third experiment overall statistical informa-
 68 tion in the absence of local information was not
 69 used. These results showed that in this task, local
 70 processes controlled behavior more precisely and
 71 more rationally than overall processes.

72 These results from pigeons corresponded closely
 73 to those from human participants (Hunt & Aslin,
 74 2001). Accordingly, the serial response time task
 75 appears to be a marvelously efficient procedure for
 76 the study of "anticipation" in nonhuman animals
 77 and for discovering properties of a general statisti-
 78 cal-learning mechanism. As Froehlich et al. (2004,
 79 p. 44) concluded, "It no doubt would be asking too
 80 much to expect universal similarity in statistical
 81 learning mechanisms across an extremely wide range
 82 of species. The present results, however, encourage
 83 the view that the universality of the likelihood esti-
 84 mation problem animals face in nature may have
 85 generated surprisingly similar likelihood estimation
 86 mechanisms." This conclusion is virtually a defining
 87 exemplar of what "mental continuity" means, and
 88 in this case, the continuity is in terms of local
 89 features of the behavior stream.

90 We found these results to be so encouraging that
 91 we subsequently conducted two more experiments
 92 using the same basic serial response time task
 93 (Shimp, Froehlich, & Herbranson, 2007). Both
 94 experiments examined how incentive, in the form
 95 of anticipated reinforcement, affected information
 96 processing. The first experiment varied the overall
 97 probability of reinforcement in a task where the spa-
 98 tial location of the target lit key varied with equal
 99 probabilities over the three possible locations.
 100 Overall response time was a linear function of over-
 101 all probability of reinforcement, in this context of a
 102 random task without any local sequential structure.
 103 So, unlike in the case in Froehlich et al., where over-
 104 all base rate of a target location had no effect on
 105 response time in the random task where one target
 106 location did not provide information about the

1 subsequent location, and overall reinforcement was
 2 held constant, overall reinforcement probability in
 3 the equal-probability version of the same task did
 4 affect overall response time. The latter outcome is an
 5 example of an overall causal relation in the absence
 6 of local contingencies. A virtue of the serial response
 7 time task is that it permits the separate manipula-
 8 tion of effects of local and overall statistical param-
 9 eters so that this kind of overall control can be
 10 identified. Much more work obviously needs to be
 11 conducted on the generality of these two phenom-
 12 ena, control by overall reinforcement probability
 13 and base-rate neglect.

14 The second experiment further explored the
 15 extent to which the serial response time task could
 16 reveal how incentive in the form of information
 17 about anticipated reinforcement affects perfor-
 18 mance. The second experiment varied incentive in
 19 the form of likelihood of reinforcement, on an item-
 20 by-item, moment-to-moment, basis, instead of on
 21 an overall basis as in the first experiment. That is, in
 22 the second experiment, different serial positions in a
 23 nine-item list were associated with different rein-
 24 forcement probabilities. We were startled by the
 25 elegance with which information theory could
 26 describe the outcome. Response time was a linear
 27 function of momentary amount of information, in
 28 accordance with the Hick-Hyman law (Hick, 1952;
 29 Hyman, 1953), implying that pigeons processed
 30 momentary statistical information at a constant
 31 rate, with more information taking longer process-
 32 ing time (Fig. 34.5). We think these results, com-
 33 bined with other avian results interpreted in terms
 34 of information theory (Vickrey & Neuringer, 2000;
 35 Young & Wasserman, 2001), strongly encourage for

36 two reasons further examination of the dynamics of
 37 behavior streams in terms of the local processing of
 38 statistical information. First, the successful applica-
 39 tion of the Hick-Hyman law to both the linear
 40 functions relating response time to overall and local
 41 reinforcement probability is to our knowledge the
 42 first conceptual unification of overall or “molar”
 43 analyses and local or “molecular” analyses in terms
 44 of information processing. Our results suggest
 45 pigeons may process both kinds of information,
 46 local incentive and overall incentive in the form of
 47 anticipated likelihood of reinforcement, at constant
 48 rates. Second, the overall results, ours and those of
 49 others, using the serial response time task with non-
 50 human animals strongly encourage the use of the
 51 mental continuity idea as a heuristic to discover new
 52 similarities in mental life across species.

53 We are not aware of corresponding results in the
 54 human literature, where it is relatively rare to
 55 manipulate a variable such as reinforcement proba-
 56 bility, either local or overall. Our results suggest that
 57 anticipated reinforcement probability, like any other
 58 probability, may be viewed in terms of amount of
 59 information (see equation 1 in Shimp et al., 2007).
 60 We find it particularly interesting that there may as
 61 yet be no human equivalent to the present results
 62 obtained from pigeons, because the idea that infor-
 63 mation is an incentive is not new. The current era is
 64 not infrequently referred to as the “information
 65 age,” and the term “information arms race” also
 66 appears. In economic theory, it plays a large and
 67 prominent role. Indeed, the importance of this idea
 68 is such that perhaps we may be forgiven for specu-
 69 lating that the present results provide some impor-
 70 tant comparative insight into the workings of the

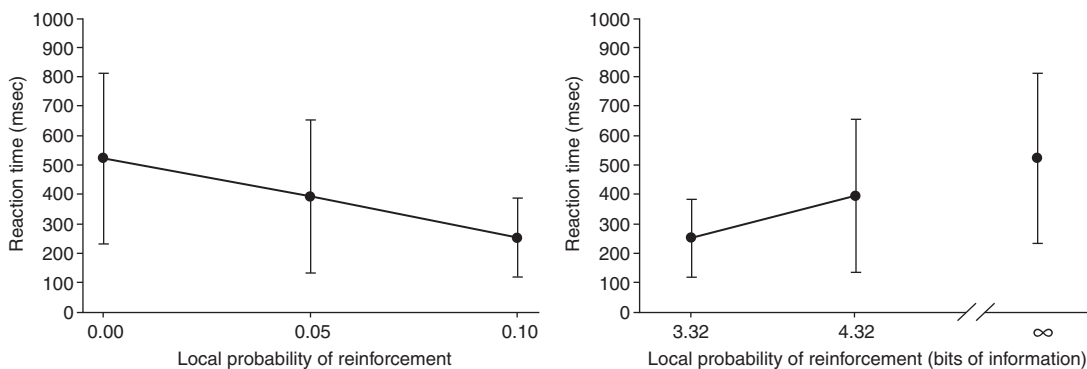


Fig. 34.5 Results from Experiment 2 of Shimp, Froehlich, and Herbranson (2007). *Left panel:* Local mean median reaction time averaged over four birds and the last 5 days of a condition, plotted as a function of the local probability of reinforcement. *Right panel:* The same data, plotted in terms of amount of information (number of bits). Information theory predicts a negative slope in the left panel and a correspondingly positive slope in the right panel.

1 stock market and other human activities where there
 2 is a premium placed on the value of information.
 3 Perhaps there is a similarity between an investor
 4 finding incentive to acquire information about the
 5 likelihood of a business venture succeeding or fail-
 6 ing, and a pigeon finding incentive to acquire infor-
 7 mation about the likelihood of reinforcement. In
 8 both cases, perhaps an organism learns statistical
 9 information because it is an incentive that facilitates
 10 anticipating subsequent reinforcement.

11 The serial response time task might serve as a
 12 useful model for the study of fundamental activities
 13 other than economic behavior if it can reveal prop-
 14 erties of a basic statistical learning mechanism. This
 15 mechanism has been speculated to have evolved to
 16 enable organisms to adapt to environments in which
 17 predation or predator avoidance, food availability,
 18 mating, and other basic activities require estimation
 19 of statistical likelihoods. It has been speculated that
 20 such a mechanism may have contributed to the evo-
 21 lution of natural language because human infants
 22 display statistical learning about sequential events
 23 with very little laboratory training.

24 We think the rapid speed with which pigeons
 25 learn the serial response time task suggests it may be
 26 a method of unsurpassed convenience for studying
 27 the behavior stream in terms of local sequential
 28 behaviors and dynamic mental information process-
 29 ing; within several dozens of trials and not too many
 30 minutes, a pigeon can be demonstrated to be learn-
 31 ing important statistical information. In addition,
 32 we speculate the task might help us to understand
 33 the difference between implicit and explicit knowl-
 34 edge of sequential information. We believe it would
 35 not be too difficult to learn whether pigeons in the
 36 serial response time task “know” or are “aware of”
 37 the statistical knowledge they learn in this task. We
 38 think procedures could be developed to ask animals
 39 questions about “what they know” about the statisti-
 40 cal information they have learned, or about what
 41 they anticipate happening next, analogous to proce-
 42 dures that have been developed to ask them what
 43 they know about what they have recently done
 44 (Shimp, 1984a). Thus, we think the serial response
 45 time task, along with the AGL task described above,
 46 are potentially two valuable methods for the study
 47 of implicit learning in pigeons, just as they are with
 48 human participants.

49 **A Dynamic Interactive Systems Theory**

50 What kind of theory can describe a stream of behavior
 51 and the moment-to-moment cognitive processes that
 52 interact with it? We chose computational-processing,

computer-simulation methods as the most likely to 53
 have the required power and flexibility. Our goal 54
 was to develop a computer simulation model that, 55
 placed in control of the behavior of a suitable robot, 56
 could generate behavior streams resembling those of 57
 real experimental subjects. 58

Assumptions 59

We chose assumptions that we knew were oversim- 60
 plifications but that were individually well known 61
 and generally supported by great bodies of empirical 62
 evidence. For this brief summary, we concentrate on 63
 how different versions have been basically the same, 64
 and delete the relatively minor details of how they 65
 have differed. 66

1. “Mental representation” of a stimulus. 67
 When the “organism” defined by the theory 68
 perceives a stimulus, it samples a corresponding 69
 set of theoretical stimulus elements, and some or 70
 all of its elements are “activated.” How these 71
 elements are functionally related and organized is 72
 assumed to be simpler than is probably the case. 73

In different versions they have been assumed either 74
 to be independent with respect to the sampling, 75
 forgetting, and retrieval processes described below, 76
 or to be completely dependent in the sense that the 77
 unique pattern of activated elements acts as a 78
 memory unit. 79

2. Short-term forgetting (memory for recent 80
 stimuli and behavior). As soon as a stimulus is 81
 removed, its representation starts to decay in a 82
 purely time-dependent manner. A representation 83
 is subjected to decay every small unit of time. 84
 How exactly it decays has depended on the 85
 version of the theory. 86

3. Base rate of responding. The simulated 87
 organism is assumed to respond randomly at a low 88
 rate when it first confronts a task. This assumption 89
 ensures that the simulated organism, or simulated 90
 robot, will in fact contact the reinforcement 91
 contingency. 92

4. Response rule (how an organism responds 93
 per unit of time given the associative status of the 94
 representations it “experiences”). The theoretical 95
 organism is assumed to respond with a high 96
 probability if it encounters in any small unit of 97
 time a stimulus the representation of which has 98
 become associated with reinforcement. Otherwise, 99
 if the representation is not associated with 100
 reinforcement, the probability of a response is low. 101

5. Associative learning (how stimuli change 102
 their associative meanings as a function of 103

behavioral experience with reinforcement). The theoretical organism is assumed to associate the currently activated stimulus elements with reinforcement when it emits a response and is reinforced. Reinforcement simply consists of setting an entry in a table equal to one. This table keeps track of which sets of elements are associated with reinforcement and which are not. If there is more than one available response, the table of associations keeps track of which sets of elements are associated with which responses.

6. Unlearning (how stimuli change their associative meanings as a function of behavioral experience with non reinforcement). When the theoretical organism responds to a set of elements associated with reinforcement but is not reinforced, the representation's association with reinforcement is assumed to change with some probability and become associated instead with non reinforcement, in which case the corresponding entry in the table of associative memories is set to zero.

Further details of different versions may be found in Shimp (1978, 1979, 1981, 1992, 1994), Shimp, Childers, and Hightower (1990), and Shimp and Friedrich (1993). All the versions generate simulated behavior streams that can be compared to the performances of real organisms.

Theoretical Successes

This family of behaving theories has generated a wide range of performances that match real performances at least qualitatively and often quantitatively. It has learned new behavioral units consisting of temporal patterns (Shimp, 1978, 1979, 1981, 1984b), it has produced the correct functions relating these units to local and overall rates of reinforcement (Shimp, 1978, 1979, 1984c, 1994), and it has demonstrated the kind of overall "undermatching" that real organisms often display in choice situations. It has demonstrated correct switching performances in choice situations (Shimp, 1984b, 1992). It handles several kinds of outcomes in temporal psychophysics, including temporal discrimination, temporal bisection, and the constancy of the Weber fraction (Shimp, 1978, 1981). It has described various spatial attention phenomena, including the validity effect and the alerting effect and of course it learned to perform the spatial attention task in the first place (Shimp & Friedrich, 1993). And, it has explained how an organism allocates time to different behaviors, each of which takes up a different amount of time (Shimp, 1979).

In all these and several other cases, the "behaving theory" generated a behavior stream from elementary, local, dynamic processes interacting in time, and this stream when analyzed was seen to have characteristics similar to those of behavior of real organisms. As is the case with behaving theories in general (e.g., see Catania, 2005, and MacDonall, Goodell, & Juliano, 2006), "behavior" emerges from interacting basic processes and is not assumed to directly describe any theoretical process.

We think this breadth compares favorably to that of other computational processing theories, especially taking into account that the theory integrates local and overall phenomena *and* integrates animal and human phenomena (Shimp, Childers, & Hightower, 1990; Shimp & Friedrich, 1993). The theory integrates these research literatures that are so different that in several cases, one literature does not even acknowledge through cross-references the existence of the other, as in the case of temporal bisection and spatial attention literatures, or the behavioral unit literature and the literature on switching performances in choice tasks. Yet it will not take but a moment for a reader to think of additional challenges the theory should be made to face. However, we emphasize that making a theory face a challenge is not the same as "testing" it. We have not developed theories in order to test them, on the grounds that the entire deductive "hypothesis testing" and "theory testing" program is highly problematic (Benham & Shimp, 2004). We have developed them instead to show how specific performances can be conceptualized and interpreted as the outcome of more general local processes. In our judgment, the challenge our theory faces is not a "test" but how it can be revised to retain a set of simple assumptions while handling a broader range of the phenomena we have described here, including the differences between implicit and explicit performances (self-reports of one's own performances), categorizations in the randomization task, AGL, and performances in the serial response time task. We think an inspiring goal is to develop a computational-processing, computer-simulation, behaving theory that would conceptually integrate these diverse phenomena, clarify the causal mechanisms underlying the behavior stream, and more fully legitimize behavior analysis and comparative cognition as sciences.

As we indicated above, we believe there is great need to facilitate the development of "behaving theories" that address the continuity of behavior in time (Shimp, 1992, 2009), and as outlined above, we have

1 tried over the years to do so. In closing, we briefly
 2 describe a few of the issues that we believe are critical
 3 for continued progress on “behaving theories.”

4 First, we suggest that neither mathematical
 5 approaches involving closed-form expressions nor
 6 connectionist approaches will suffice to characterize
 7 the continuity of behavior streams. We think the
 8 former is too methodologically constraining,
 9 although that opinion might merely reflect our own
 10 limited mathematical expertise. We suspect the
 11 latter is too theoretically constraining and that it
 12 will become too computationally unwieldy when it
 13 is required to deal with the continuity of a stream of
 14 any sizeable temporal duration, meaning of as little
 15 as a few seconds. If this approach is to succeed, we
 16 suspect it will be due to the adoption of an iterative
 17 approach to determine what a connectionist theory
 18 predicts, similar to how we have used iteration in
 19 our computer simulations to discover how the
 20 theory described above behaves. As to self-organiz-
 21 ing systems theory, fractals, and other approaches,
 22 we would like to think of ourselves as open-minded
 23 but confess to being perhaps a bit old-fashioned; we
 24 prefer to base the functional components of a com-
 25 puter model on known cognitive, behavioral, or
 26 neurophysiological processes rather than assume
 27 they are the same as those in ecosystems, astrophys-
 28 ics, and viruses. The grandiose nature of claims for
 29 such universality across different scientific disci-
 30 plines can feel thrilling but in our judgment is likely
 31 to lead to disappointment.

32 Second, we suggest that it will prove difficult but
 33 essential to conceptually unify the continuity of
 34 behavior and of mental life, on the one hand, with
 35 the discontinuity produced by segmenting and
 36 chunking behavior streams into successive behav-
 37 ioral units, on the other hand. We expect future
 38 progress in behavioral science to repeat analogous
 39 previous progress in the more established sciences,
 40 once there is better understanding of how behavioral
 41 units emerge and interact continuously over time.

42 Finally, local and global analyses should not be
 43 thought of in any sense as on different “levels” cor-
 44 responding to the difference between physics and
 45 chemistry, or the difference between chemistry and
 46 biology, unless the processes and standards that
 47 define different levels in these other sciences are first
 48 shown to apply to behavior (Shimp, 2009). The
 49 mean of a distribution of numbers does not emerge
 50 from the distribution in the manner in which wave
 51 phenomena emerge from water molecules, so that
 52 the overall mean rate of responding is not an emer-
 53 gent phenomenon on some level different from

local response rates. We think it is reasonable to
 reverse the usual line of thinking that an overall
 empirical outcome stands on its own unless it can
 be shown that a local explanation is needed. We
 think it might as well be the other way around: If
 overall empirical results are to be taken seriously as
 complete, self-contained accounts of behavior, they
 need to be shown not to be derived from local phe-
 nomena. Ideally, when local effects are described, it
 would be helpful if they were linked to overall ones,
 and when overall effects are described, it would be
 helpful if it were acknowledged how they might
 derive from local ones. Thinking in terms of the
 continuity of behavior streams might help remind
 researchers of the essential need to know how to
 methodologically and theoretically unify these kinds
 of analyses.

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