Stimuli, Reinforcers, and Private Events

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Radical behaviorism considers private events to be a part of ongoing observable behavior and to share the properties of public events. Although private events cannot be measured directly, their roles in overt action can be inferred from mathematical models that relate private responses to external stimuli and reinforcers according to the same quantitative relations that characterize public operant behavior. This approach is illustrated by a model of attending to stimuli and to anticipated reinforcers in delayed matching to sample, in which the probabilities of attending are related to reinforcer rates by an expression derived from research on behavioral momentum.

Key words: private events, reinforcers, stimuli

My title plays off a paper by Davison and Nevin (1999) entitled “Stimuli, Reinforcers, and Behavior: An Integration.” It’s a complicated paper that treats the three terms of the discriminated operant similarly and proposes a comprehensive quantitative model of performance in discrete-trial conditional discriminations and free-operant schedules of reinforcement. Here, I ask whether a quantitative science of behavior can treat activities that take place inside an organism’s skin in the same integrative fashion as the public events that Michael Davison and I discussed.

To pursue quantitative analyses, we have to measure things—assign numbers to them—and the numbers have to satisfy measurement scale criteria. Ideally, the numbers assigned to various aspects of behavior should be additive on a ratio scale.

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But private events, by definition, are not amenable to direct measurement. This paper will suggest that some private events can be evaluated indirectly by quantitative inference based on the assumption that events within the skin are functionally the same as overt activities such as free-operant responses that are amenable to ratio-scale measurement.

The assumption of functional equivalence is central to radical behaviorism. In an oft-quoted passage, Skinner (1969) wrote, “An adequate science of behavior must consider events taking place within the skin of an organism, not as physiological mediators of behavior, but as part of behavior itself. ... Private and public events have the same kinds of physical dimensions” (p. 228). More recently, Baum (1994) wrote, “Private events, if they need to be spoken of at all, are natural and share all the properties of public behavior” (p. 47).

Why do I need to speak of them? Because I would like the science to which I have devoted my professional career to encompass my private life as well as my public actions and those of other creatures. Therefore, following Skinner, I want at least to try to treat private, personal events in the same objective, quantitative, analytic ways that our science has used to study the readily countable key pecks of pigeons.

Some personal background: I went to graduate school at Columbia in 1959 because I had read about Fechner's work in the mid-19th century and assumed that modern psychology could provide a disciplined scientific window on the relation between mind and body, or at least between private sensory experience and the public world of physics. My first graduate research project attempted to measure the chromatic properties of privately experienced colors induced by red and white Land images by allowing a subject to adjust a matching field. After a year, with Clarence Graham's guidance (and equipment), I realized that the appearance of the matching field itself was affected by the inducing images, and abandoned the project. Fortunately, Bob Berryman and Bill Cumming needed a research assistant on a grant directed by Fred Keller, so I went to work on schedules of reinforcement in rats and delayed matching to sample in pigeons.

There was a link, though, to private processes. In a draft of a subsequently published chapter that the graduate students discussed in seminars, Nat Schoenfeld and Bill Cumming argued that to understand some phenomena in the domain of perception, it was necessary to assume that overt behavior R_2 in response to some stimulus S_1 depended on an inferred intervening response R_1 and its accompanying stimuli S_2 ; the paradigm was $S_1 \rightarrow [R_1 * S_2] \rightarrow R_2$ (Schoenfeld & Cumming, 1963). At the same time, Cumming and Berryman were developing a subsequently published argument that to understand the properties of transfer to novel key colors in matching-to-sample tasks, it was necessary to assume that the pigeon was responding not to the color of the sample but to its own color-naming response to the sample, the *sample-as-coded* (Cumming & Berryman, 1965).

Also at that time at Columbia, Ralph Hefferline was studying private activities by making them public. Hefferline, Keenan, and Harford (1959) used electromyographic amplification to measure an invisibly small muscle twitch, and arranged that a subject could escape or avoid an unpleasant noise by making exactly that small-scale response, not too large and not too small. They found that the rate of occurrence of a defined twitch increased when it was effective in terminating or postponing the noise and decreased when the twitch was ineffective, without prior instructions and without the subjects' awareness that their behavior had controlled the noise. This is clear evidence that a private event, made public by electromyography, can function as an operant under the control of reinforcement contingencies.

In a subsequent study, Hefferline and Perera (1963) presented a tone when the subject emitted the proper amplitude of an invisibly small thumb twitch, where the tone served as a signal to press a key to receive feedback plus points. In effect, this is a heterogeneous chain with private and public events: twitch $\rightarrow$ light $\rightarrow$ key press $\rightarrow$ reinforcement. After subjects mastered the task, the tone intensity was progressively diminished to zero, but subjects continued to press the key after emitting thumb twitches, and 1 subject reported that he still heard the tone. Thus, a private response, made public by electromyography, could function as a discriminative stimulus for overt responding, like $[R_1 * S_2]$ in the Schoenfeld-Cumming paradigm.

Now, let's bring these properties of private events to bear on pigeons' performance on delayed matching-to-sample (DMTS) tasks, which are widely used for the study of short-term working memory. Rather than attempting direct measurement of private stimuli and responses in the pigeon, I am going to proceed by inference, making the strong assump-

tion that the determiners of private events follow the same quantitative laws as the determiners of overt operant behavior.

The quantitative characterization of overt operant behavior is based on three decades of research on response rates and resistance to change in multiple schedules of reinforcement, which permit within-subject, within-session comparison of the effects of different conditions of reinforcement in the schedule components (Nevin & Grace, 2000). An expanded paradigm known as multiple variable-interval (VI) DMTS, introduced by Schaal, Odum, and Shahan (2000), provides data on DMTS accuracy as well as the rate of key pecking that produces DMTS trials. Odum, Shahan, and Nevin (2005) extended the paradigm to compare reinforcer effects on resistance to change of DMTS accuracy as well as response rate when short-term disrupters were introduced. As depicted in Figure 1, pigeons pecked a center key to produce DMTS trials with yellow or blue sample and comparison stimuli according to a multiple VI 30-s schedule. In the rich component, the center key was red, and pecks to the comparison of the same color as the sample produced food with probability of .9. In the lean component, the center key was green, and correct pecks produced food with probability of .1. Unreinforced correct responses and all errors were followed by a brief blackout. Retention intervals varying from 0.1 to 8 s were inserted between sample offset and comparison onset; the center key was lighted with the same color, red or green, that was present during the VI segments of the component. Components alternated after four DMTS trials were completed, and were separated by intercomponent intervals (ICI) with all keys dark. After many training sessions, steady-state performance was disrupted by introducing response-in-

dependent food during ICIs and by discontinuing food altogether (extinction).

The major results, averaged over four pigeons, are shown in Figure 2. The left column presents the rates of responding in the rich and lean components, and shows that in the rich component, steady-state response rates were higher (top panel) and resistance to change relative to baseline was greater during disruption by ICI food (middle panel) and by extinction (bottom panel). These findings replicate many previous results with food, rather than DMTS trials, as the consequences of responding. The right column presents DMTS forgetting functions, and shows that in the rich component, steady-state accuracy was higher (top panel) and resistance to disruption relative to baseline (middle and bottom panels) was greater in the rich component, just as for response rate. These are orderly, reliable results, and could easily stand on their own, but I wanted to identify the private accompaniments of the public discriminative behavior exhibited in Figure 2.

Michael Davison, Amy Odum, and Tim Shahan joined my efforts to provide an account of private behavior that culminated (after several rejections) in a theoretical article in the *Journal of the Experimental Analysis of Behavior (JEAB)*; Nevin, Davison, Odum, & Shahan, 2007). In that article, we argued that accurate DMTS performance necessarily involves attending to the samples and comparisons, and that short-term forgetting can be understood in relation to attentional processes during the retention interval. As suggested in Figure 3, attending to the sample includes looking for it (i.e., emitting observing behavior) during the VI before trial onset and discriminating its relevant properties (e.g., color) when it is present. Then, a private coding response is made to the sample, and the subject attends to

The VI DMTS paradigm

Figure 1. A schematic representation of the multiple VI DMTS paradigm for pigeons, where components are signaled by red or green lights on the center key and pecking produces DMTS trials according to a VI schedule. The probability of reinforcement for correct comparison choices depends on whether the rich or lean component is in effect. Note that the key color signaling rich versus lean components is present during the retention interval as well as the VI.

Figure 2. The upper panels show average VI response rates and DMTS forgetting functions, where accuracy is measured as $\log d$, in rich and lean components of multiple VI DMTS (from Odum et al., 2005). The middle panels express response rates and DMTS accuracies at each retention interval during 10 sessions with intercomponent food, relative to baseline, and the lower panels present data during 10 sessions of extinction in the same way.

Figure 3. A time-line diagram showing the stimulus presentations and assumed private events during a VI DMTS trial; the times during which disruptors may operate are indicated at the bottom. See text for explanation and rationale.

the stimuli accompanying that coding response during the retention interval. It's like looking for a number (the sample) in a phone book, finding it, and then rehearsing it by repeating it to yourself while walking across the room to a phone—and of course you may forget the number if someone interrupts and diverts your attending behavior elsewhere. On this view, forgetting in short-term working memory results from a failure of attending to the sample-as-coded, whatever the code.

In addition, the diagram suggests that the subject attends to the comparisons by emitting observing behavior such as orienting toward their locations during the retention interval and by discriminating their relevant properties during their presentation before responding. That is like looking across the room to see where the phone is and then punching in the number (the comparisons). If you do not attend to the phone's keypad and

hit the wrong number key, you might just as well have forgotten the number.

Finally, the diagram indicates two sorts of potential disruptors: general background factors such as variations in the level of motivation or competition from other activities that affect attending throughout the VI DMTS cycle, and events specific to the retention interval such as distraction by internal or external stimuli that occur with constant probability in time so that the cumulative likelihood of disruption increases with the length of the retention interval.

The notion of attending during the retention interval may be difficult to accept because there is no stimulus present; the only thing a subject can attend to is its own behavior, which may be presumed to have accompanying stimuli that cannot be measured directly. But whatever it is that the subject is doing during the retention interval, that behavior

(and therefore its accompanying stimuli) can come under control by external stimuli correlated with reinforcers, just like overt key pecking. To demonstrate this, Nevin et al. (2007) reversed the center-key colors across components during the retention interval only, with the reinforcement schedules unchanged, so that the probability of reinforcement for a correct choice was correctly signaled by the VI color and incorrectly signaled by the retention-interval color. This cue reversal was in effect for 10 sessions, followed by a return to baseline. Figure 4 shows that the rich-component forgetting function went down and the lean-component function went up, suggesting that the probability of attending had decreased in rich and increased in lean. Relative to the prereversal baseline, the magnitude of the effect increased as the retention interval lengthened, which makes sense because there is not much exposure to the reversed cues at short intervals.

Because retention-interval attending might be indexed by overt key pecking, we recorded the rate of pecking the center key during the retention interval and found that on average, the rate went down in rich and up in lean during cue reversal. However, the effect was inconsistent across birds, and the correlation between the magnitudes of individual changes in accuracy and retention-interval pecking was -0.1 across 5 pigeons. Thus, overt pecking did not serve as a reliable correlate of attending during reversal.

In sum, it appears that some unspecified private activities subsumed under the term *attending* resemble conventional public operants in their sensitivity to the rate of public reinforcers signaled by public stimuli.

To develop a complete account of DMTS performance that includes unmeasured private events, Nevin et al. (2007) assumed that attending to the samples and comparisons, as

characterized in Figure 3, depended directly on the rate of reinforcement, and that the reduction in attending produced by short-term general disrupters such as ICI food and extinction depended inversely on the rate of reinforcement. More specifically, the effects of reinforcement and disruption on probabilities of attending were characterized by an exponential function derived from research on the resistance to change of key-pecking rates in multiple schedules (Nevin, 1992; Nevin & Grace, 2000). We then assumed that if the pigeon attended to samples and comparisons on a given trial with highly distinctive stimuli such as key colors, it responded correctly to the comparison that matched the sample; if the pigeon did not attend, it responded at random. Here are some ordinal predictions.

First, because the probability of attending depends directly on the rate of reinforcement, and because accuracy depends directly on attending, accuracy should be greater in the rich component of multiple VI DMTS. Second, because disruptive effects depend inversely on reinforcer rate, attending—and therefore accuracy—should be reduced to a lesser extent, relative to steady-state baseline, in the rich component during tests of resistance to change.

More quantitative predictions are shown in Figure 5. Because the theoretical derivations and applications to DMTS data are tedious and have been described in detail by Nevin et al. (2007), I will not go into them here, but will characterize their ordinal predictions and present model simulations of the data shown in Figures 2 and 4. Interested readers should consult the Appendix for a more complete account.

The top panel presents forgetting functions predicted by the model for rich [$p(\text{rft}) = .9$] and lean [$p(\text{rft}) = .1$] components that correspond quite well to the data of Odum et al. (2005) shown in Figure 2. The middle panel shows that DMTS accuracy is

Figure 4. The upper panel presents forgetting functions, where accuracy is measured as $\log d$, obtained before and during reversal of the center key colors during the retention interval so that the actual reinforcer probabilities were falsely signaled. The lower panel expresses accuracy during cue reversal relative to baseline (from Nevin et al., 2007).

Figure 5. The upper panel presents a model simulation of baseline multiple VI DMTS data (Figure 2, upper right panel). The middle panel presents a simulation of the effects of general disrupters (Figure 2, middle and lower

predicted to be more resistant to change in the rich component, relative to baseline, when performance is challenged by a general disrupter that is not specific to the retention interval; the predicted functions correspond at least ordinally to the data for ICI food and extinction in Figure 2. Finally, the bottom panel shows that when retention-interval cues are reversed to signal, falsely, the opposite of the scheduled reinforcer probability, accuracy goes up relative to baseline in the lean component and down in the rich component, in accord with results presented in Figure 4.

In sum, the model does a respectable job of simulating empirical findings, and the assumption that unmeasured private attending is related to reinforcement and disruption in the same way as public responding is supported by the covariation of response rates and DMTS accuracy in the data of Odum et al. (2005). Moreover, the retention-interval cue-reversal data of Nevin et al. (2007) suggest that attending to the sample-as-coded can come under control by stimuli signaling different reinforcer rates in the subject's history, in accordance with model assumptions. Thus, the model can provide a quantitative account of private events in DMTS trials.

The model is readily expanded to encompass attending to outcome expectancies as well as to trial stimuli. Many studies have shown that if correct responses to comparison C_1 following sample S_1 lead to qualitatively or quantitatively different outcomes from correct responses to C_2 following S_2 , accuracy is consistently higher than if the outcomes are the same. For example, Nevin, Ward,

right panels), and the lower panel presents a simulation of the effects of retention-interval cue reversal (Figure 4, lower panel). See the Appendix for particulars of the simulations.

Figure 6. The upper panel presents forgetting functions, where accuracy is measured as $\log d$, with same (SO) or different (DO) probabilities of reinforcement correlated with the sample key colors in the components of multiple VI DMTS (from Nevin et al., in press). The lower panel presents simulated forgetting functions. See the Appendix for particulars of the simulations.

Jimenez-Gomez, Odum, and Shahan (in press, Experiment 3) arranged that in one component of multiple VI DMTS, blue samples signaled that correct matches would produce food with probability of .9, whereas yellow samples signaled that correct matches would produce food with probability of .1. In the other component, all correct matches produced food with probability of .5, so that total food availability was equated between components. The average forgetting functions are displayed in the top panel of Figure 6, showing that accuracy in the different-outcome component was consistently higher than in the same-outcome component, with differences becoming especially clear at longer retention intervals. This basic finding, known as the differential outcome effect, has been repeated within and between subjects in a variety of discrimination paradigms with dogs, horses, and rats as well as pigeons, children with autism, and adults with dementia-related memory deficits (for review see Urcuioli, 2005).

Peterson and Trapold (1980) accounted for the differential outcome effect by noting that when S_1 predicts Outcome A and S_2 predicts Outcome B, different private responses appropriate to the anticipated outcomes may be engendered by those samples, and the private stimuli accompanying those responses can serve as cues for correct responses at the end of a retention interval. Thus, in the different-outcome component, there are redundant cues arising from the sample-color-as-coded and the sample-based outcome expectancy. If the outcomes are substantially different, the outcome-expectancy cues will be distinctive (e.g., feelings such as joy vs. woe). If attending to the sample-as-coded and to the sample-based outcome expectancy are independent, either can serve as a cue for the correct choice of comparison, so that if attending to one is disrupted during the retention interval, the other re-

mains to guide correct choice. But because the outcomes are the same for both samples in the same-outcome component, outcome-expectancy cues will be the same and cannot serve as differential cues for the correct comparison. Therefore, differential outcomes should sustain higher accuracies, especially as the retention interval lengthens and the opportunity for distraction increases. The lower panel of Figure 6 shows that our model, using exactly the same parameters as for the VI DMTS baseline (Figure 5), does a good job of simulating the within-subject differential outcome effect. So it appears that the general theory advanced above can incorporate private attending to internal cues based on expected outcomes as well as attending to external key-color cues and the internal stimuli accompanying private coding responses.

How (if at all) does the line of research and theory described here actually contribute to the radical behaviorist effort to incorporate private events into a science of behavior? Unlike Hefferline and his colleagues, I have not made private events accessible to direct measurement. Instead, I have offered a way to treat private events indirectly by making them essential components of a model of behavior, just as private events are a part of behavior itself.

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APPENDIX

A condensed version of the model of DMTS performance proposed by Nevin et al. (2007) is presented here to support the arguments in the text. Readers seeking a complete account should consult the original article.

The model assumes that a subject must attend to both samples and comparisons in order to respond correctly in a DMTS trial, and makes some detailed assumptions about when attending to the samples and comparisons occurs within a trial (see Figure 3). It also assumes that the unmeasured private behavior of attending depends directly on the rate of reinforcement and inversely on the magnitude of a disrupter within DMTS trials in the same way as overt free-operant responding.

Nevin (1992) proposed the following equation to characterize resistance to change, relative to baseline, in a number of multiple-schedule studies:

$$\log(B_x/B_o) = -x / (r_s/r_a)^b, \quad (1)$$

where B_x and B_o are response rates during disruption and baseline, respectively; x is the value of a disrupter, with negative sign indicating that it reduces response rate; r_s is the reinforcer rate in a defined target situation; and r_a is the overall average reinforcer rate in the experimental context within which that situation occurs.

To address absolute rate of responding rather than log proportion of baseline, Equation 1 is exponentiated:

$$B = k' \exp \left[-x / (r_s/r_a)^b \right], \quad (2)$$

where B is response rate, and k' is the asymptote of response rate as r_s increases without limit. Nevin and Grace (2005) used Equation 2 to characterize some aspects of performance during repeated extinction tests.

Nevin et al. (2007) proposed that the probabilities of attending to samples and comparisons are related to reinforcer rates according to versions of Equation 2. Specifically, on any given trial, the probability of attending to the sample, $p(A_s)$, is given by

$$p(A_s) = \exp\left(\frac{-x - qt}{(r_s/r_a)^b}\right), \quad (3)$$

where sample-related reinforcer rate r_s (i.e., reinforcers per session divided by the time preceding, during, and following sample presentation until onset of the comparisons) is expressed relative to overall average reinforcer rate for an entire session, r_a . Just as for response rate (Equation 2), attending to the samples depends directly on the value of r_s relative to r_a , and inversely on a general background disrupter x . In addition, to apply the equation to DMTS, the numerator of the exponent of Equation 3 includes a separate disrupter qt that is specific to the retention interval, where q represents disruption per unit time and t is the duration of the retention interval.

Likewise, the probability of attending to the comparisons is given by

$$p(A_c) = \exp\left(\frac{-z - vt}{(r_c/r_s)^b}\right), \quad (4)$$

where comparison-related reinforcer rate r_c (i.e., reinforcers per session divided by time from sample offset to comparison offset) is expressed relative to r_s , the reinforcer rate in the context in which comparisons appear. Attending to the comparisons depends directly on the value of r_c relative to r_s , and inversely on a general background disrupter z (which may differ from x) and by a separate disrupter vt , where v (which may differ from q) represents disruption per unit time within the retention interval and t is the duration of the retention interval. On the basis of many previous analyses of free-operant response rate, the value of b is set at 0.5 in both equations. The use of separate retention-interval disruption parameters for the samples and comparisons reflects the possibility that attending to the sample-as-coded and

observing the comparisons may be distinguishable processes.

To move from equations that characterize the probabilities of attending on a given trial to empirical measures of accuracy over many trials during one or more sessions, the model assumes that if the subject attends to both sample and comparisons on a given trial in a standard DMTS procedure with easily discriminable stimuli, it responds correctly. If it does not attend either to the sample or to the comparisons, it responds randomly. Discrimination accuracy is predicted by a weighted average of trials with and without attending given by Equations 3 and 4. The simulations of DMTS accuracy in multiple-schedule components with different reinforcer probabilities presented in Figure 5 (top panel) were based on parameter values $x = 0.02$, $q = 0.04$, $z = 0.05$, and $v = 0.0$ in those equations. By inspection, the simulation captures the main features of the data.

To simulate the added effects of general background disrupters such as ICI food or extinction (Figure 5, middle panel), the values of x and z were increased by 0.10 while the values of q and v , representing distractors during the retention interval, were unchanged. Although the data for ICI food and extinction (Figure 2) are not mimicked in detail, the general result—greater accuracy, relative to baseline, in the rich component—is correctly simulated.

To simulate the effects of reversing retention-interval cues, the value of r_s was expressed as a weighted average of the reinforcer rate correctly signaled by key colors presented during the VI before sample onset and the reinforcer rate falsely signaled by key colors during the retention interval. To capture the general nature of the findings, it was necessary to increase the values of q and v , representing distraction or disruption during the retention interval, by 0.04, which may plausibly be identified with

disturbance created by cue conflict. The resulting shifts in accuracy relative to baseline (Figure 5, bottom panel) accord well with the data.

To simulate the differential outcome effect (Figure 6, top panel), the model assumes that in the differential-outcome (DO) component, the probability of attending to cues arising from expecting different outcomes, designated $p(A_e)$, follows exactly the same equation, with the same parameter values, as for attending to the sample key colors, $p(A_s)$. Thus, in the DO component, the probability of attending either to the samples, or to the correlated expectancy cues, or to both is given by the sum of the probabilities of attending to either minus their product: $p(A_{se}) = p(A_s) + p(A_e) - p(A_s)*p(A_e)$. The model assumes further that attending to the comparisons is determined identically in both DO and same-outcome

(SO) components by Equation 4. Clearly, if all parameters in Equation 3 are the same in both DO and SO components, $p(A_{se})$ in the DO component must be greater than $p(A_s)$ in the SO component, providing a basis for the differential outcome effect. Simulated forgetting functions for DO and SO components, using exactly the same parameter values as for the DMTS baseline data (Figure 5, top), are presented in the lower panel of Figure 6. The simulations accord well with the data.

For readers who wish to explore the quantitative consequences of other assumptions about attending to DMTS stimuli, a worksheet showing the sequence of model calculations in full detail (in Microsoft Excel) is available at the *JEAB* Web site (seab.envmed.rochester.edu/jeab/extensions/nevin.html).