Computer Simulations of Verbal Behavior for Research and Persuasion

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Various reasons have been suggested for the failure of Skinner's (1957) revolutionary analysis of verbal behavior and subsequent research to persuade most of the world of its value (e.g., Eshleman, 1991; Oah & Dickinson, 1989). Campbell and Stanley (1963) argued that the challenge in strengthening a theory is to rule out plausible rival explanations for observed results. It has been far too easy to dismiss an operant theory of verbal behavior, given at least two alternative explanations that have seemed impossible to rule out: (a) specialized mechanisms in the brain, such as Chomsky's (1957) miraculous language acquisition device, and (b) uncontrolled variables in the vast, unrecorded, and ethically uncontrollable histories of young human subjects.

Computer simulations of operant behavior can rule out both of these explanations. An operant computer organism can have exactly the properties we specify and no more, ruling out the first alternative explanation. We can also control and record every detail of a computer organism's history while creating environmental histories that isolate causal relations, ruling out the second alternative explanation. When an operant organism of our own design acquires verbal behavior in an environment under our complete control, we still have not proven that this is how humans acquire verbal behavior, but we have proven that operant learning is *sufficient* to produce the behavior. Sufficiency proofs refute insufficiency claims

such as Chomsky's (1959) "poverty of the stimulus" argument. The more similar the history is to human histories, and the more similar the acquisition pattern is to human patterns, the stronger our argument becomes. If competing theorists are not able to prove even the sufficiency of their theories in simulations, our operant approach should finally attract serious attention.

I have been conducting operant simulations of the acquisition of verbal behavior for several years. These simulations are closely related to work in neural networks, especially designs based on reinforcement learning (Sutton & Barto, 1998), although I emphasize that mine is a behavioral, not a neural, model (Hutchison, 1997c). Skinner's (1957) conceptual framework has been perfectly suited to designing these simulations,¹ and they have been uniformly successful in producing a range of verbal phenomena. They have also confirmed Skinner's point that the complexity of environment-behavior interactions makes the study of verbal behavior, and even thinking about it, extremely difficult (1957, p. 11). I have become convinced that computer models of operant formulations are essential for organizing our thinking about these complex interactions, and that our science cannot make much further progress without them (Hutchison, 1997a).

¹Consistent with Skinner's core assertion that verbal behavior is simply operant behavior, my operant formulation has no additional elements just for verbal behavior. Hayes (e.g., 1994) has argued that possible difficulties with Skinner's definition of verbal behavior invalidate his analysis, as if it had to be defined as a separate field. Although some people might like to have a better definition for various reasons, the only essential issue is whether the general operant approach enables us to predict and control the behaviors of interest.

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The simulations use the 7G Operant Agent Toolkit (Hutchison, 1997b), written in the Java language to run on any computer. The basic concept is that the organism (or *agent*) has sensors and movements and a matrix or network of controlling relations between them. The strength and valence of the relations are increased and decreased as a result of events that have been defined as primary reinforcers and punishers for the agent. The resulting *conditioned* values enable conditioned reinforcement and punishment, which are essential in realistic operant behavior. I describe (1997a) how operant concepts produced the design, and the documentation and source code enable users to examine it in detail and to try variations. The agent exhibits a wide range of behavioral phenomena, including those necessary for fairly sophisticated verbal behavior. The following simulations show what can be done with this fairly simple operant model.

1. Skinner suggested that an important process in early language acquisition was the "automatic" reinforcement of vocal responses by the sounds produced (1957, p. 58). The sounds are assumed to have conditioned value from their predictive relation to reinforcers provided by caregivers. To test this formulation, a simulation arranged for vocal stimuli to be predictive of a higher rate of reinforcer delivery, independent of responding. The sounds did acquire conditioned value, and in a posttest, familiar sounds had more value than novel sound patterns such as those of a foreign language (Hutchison, 1997b, "BabyHear" demo). Many of the results of these infant speech simulations are closely related to phenomena in developmental phonology, a field that seems to be very compatible with our views (Vihman, 1996).

2. Skinner described the acquisition of minimal verbal repertoires (1957, pp. 61-64) as a very important part of later verbal behavior. For example, in a minimal echoic repertoire, small stimulus units such as phoneme sounds acquire stimulus control over corresponding sets of vocal tract responses that produce them (cf. imitation). I have found it a good practical strategy to begin almost all verbal training simulations with minimal repertoires, and they are established

quite readily by a straightforward process of discrimination. There also seems to be a brief but important role for parents echoing the child's novel vocalizations, as Hartup and Coates (1972) suggested, because the probability of a child echoing a parent's novel sound is too low to maintain the parent's behavior when the sound has never been emitted before. A simulation (Hutchison, 1997b, "ParentEcho" demo) showed that an echoic repertoire is acquired much faster when the caregiver reinforces, echoes, and continues to model the agent's first-time vocalizations.

3. Most verbal training – structured or, more commonly, unstructured – makes use of prompting that depends on the prior learning of a minimal echoic repertoire. For example, tacting (in the standard vernacular, naming) is commonly taught by presenting the stimulus property, such as a red object, while modeling the desired tact, *red*. When the child echoes the tact (from his or her minimal echoic repertoire), the trainer provides some reinforcing consequence, such as a hug or saying "Good!" The trainer repeats the pairing (preferably with various objects to isolate the controlling property) while fading the intensity of the prompt, until the stimulus property alone controls the correct tact. This training approach works well not only for tacts but for most verbal behaviors as well as nonverbal behaviors such as gross motor movements when minimal repertoires have been learned. In my simulations, operant agents have quickly learned to tact objects, to repeat intraverbal sequences, and to comply with verbal instructions using this prompt and fade procedure (Hutchison, 1997b, Tact, Intraverbal, and Pliance courses in "RuleFollow" demo).

4. In what may be a fundamental demonstration, an agent is trained to tact object properties, to follow verbal instructions, and to repeat intraverbal "rules" (e.g., *If red then move back*), where the conditions in the rule (in this case, red) were trained tacts and the actions in the rule (in this case, move back) were trained instructions. After this training, when a stimulus is presented, the agent tacts the stimulus, the tact evokes the rest of the intraverbal rule, and saying the action part of the rule controls the motor response

of following the instruction (Hutchison, 1997b, "RuleFollow" demo). I believe that such simulations will help us to understand the extremely important realm of instructional control or rule-governed behavior (Hayes, 1989; Skinner, 1969).

5. Chomsky (1959) claimed that Skinner's approach would fail to produce new combinations of verbal responses that had not been reinforced together, such as saying "green ball" after learning *green* and *ball* but seeing a green ball for the first time. Not only the novel combination of responses but also the ability to say them in grammatical order (not *ball green*) were supposedly impossible for Skinner's analysis. However, simulations have shown not only that operant learning produces such "generative" responding (*autoclitic* in Skinner's terminology), but also that it is learned very quickly following a process that is elegantly based on operant concepts (Hutchison, 1997b, "ColorShape" demo).

6. Relational statements such as *The tuna is left of the shark* are another challenge, because the relation between the stimuli must control a sequence of verbal responses independent of any history with the specific stimuli present. A simulation was based on Skinner's suggestion (1957, pp. 340-343) that relational tacts often have their roots in movements. The movements produce stimuli that can acquire control over the relational statement and its position in the utterance. In this example, after looking at the first object and tacting it, the most valuable response is to look at the second object (after the agent learns that tacting the same object repeatedly will not be reinforced). Looking at the second object requires an eye movement that can very naturally become a discriminative stimulus for the relational response *left*. Looking directly at the second object then strengthens the second tact, *shark*. The simulation shows how every detail of the operant control fits together to produce correct relational statements in a robust way (Hutchison, 1997b, "Relate2" demo). Just as important, the control generalizes to objects that have never been seen in those relations.

My recent work has begun to use real auditory and visual sensory events rather than abstract stimuli, and to produce real speech

sounds and motor movements. The computer agent "senses" the intensity of sound waves in speech-relevant frequency bands from 0 to about 4000 Hz, similar to a cochlea. The computer's speech uses a Trillium™ articulatory synthesizer (or a table that simulates it), which takes the set of vocal tract positions produced by the agent's movements of its simulated vocal tract (tongue, lips, etc.). This emphasis on speech as motor movements is probably necessary for many phenomena of verbal behavior. For example, "uh" and "ah" are very similar in terms of the behaviors that produce them, but are as different as "uh" and "t" when looked at simply as discrete phonemes fed into a typical speech synthesizer. These direct connections of robotic operant agents into the real world will enable us to rule out yet more skeptical explanations of our results. Apart from the theoretical importance of such extensions, the persuasive power of our demonstrations will be magnified by their ability to interact directly with people.

Besides having value for theory development and persuasion, computers that have learned verbal behavior can perform commercially valuable tasks. Stephens (1996) has long argued that commercial success of operant computer applications can increase the prestige and credibility of our field and attract students and resources, like the success of behavior analysis in business management. Existing computer programs such as speech recognition and synthesis appear to be exhibiting verbal behavior, but we recognize that the behaviors are not controlled by their consequences. For example, there are industrial object-recognition systems that can name a few mutually exclusive objects placed in front of a camera. But what would happen if a realistic visual scene were presented, with thousands of alternative tacts alone? Most of the utterances would be true but useless (e.g., "brown, red, circle, nose, chair," or more likely in a nonadaptive system, "brown, brown, brown, ..."). Useful speech requires selection by consequences of utterances that are valuable to the user. For example, a blind user would want the computer to tact *red light* (and perhaps the intraverbal, *Don't cross*) when approaching a street crossing. As another example, speech

recognition systems have major problems when more than one person speaks at a time. In an operant agent, the utterances of one speaker greatly increase the strength of hearing the same speaker's other utterances due to their functional relationships (William Potter, personal communication, June, 1997). As another broad example, neural networks learn by direct contingency shaping, but they cannot make use of the vast amount of verbally based information (instruction, rules) that would be extremely valuable and efficient. My simulations, especially the fourth, have shown how to give neural networks both contingency-shaping and rule-governed repertoires. There are many other technical advantages of agents built with an operant perspective (e.g., Hutchison, 1995).

In summary, computer simulations offer at least three unique contributions to verbal behavior. We can effectively analyze the acquisition of verbal behavior despite the explosive complexity of situations and history. We can persuade others that our analysis is plausible by ruling out rival theories. We can produce computer systems with valuable verbal and nonverbal behavior. I believe that simulations will be a critical factor in sparking the verbal behavior revolution at long last.

REFERENCES

- Campbell, D. T., & Stanley, J. C. (1963). *Experimental and quasi-experimental designs for research*. Chicago: Rand McNally.
- Chomsky, N. (1957). *Syntactic structures*. The Hague: Mouton.
- Chomsky, N. A. (1959). Review of *Verbal Behavior*, by B. F. Skinner. *Language*, 35, 26-58.
- Eshleman, J. W. (1991). Quantified trends in the history of verbal behavior research. *The Analysis of Verbal Behavior*, 9, 61-80.
- Hartup, W. W., & Coates, B. (1972). Imitation: Arguments for a developmental approach. In R. D. Parke (Ed.), *Recent trends in social learning theory* (pp. 63-75). New York: Academic.
- Hayes, S. C. (Ed.). (1989). *Rule-governed behavior: Cognition, contingencies, and instructional control*. New York: Plenum.
- Hayes, S. C. (1994). Relational frame theory: A functional approach to verbal events. In S. C. Hayes, L. J. Hayes, M. Sato, & K. Ono (Eds.), *Behavior analysis of language and cognition* (pp. 9-30). Reno, NV: Context Press.
- Hutchison, W. R. (1995). *Teaching an agent to speak and listen with understanding: Why and how?* Online proceedings of the Intelligent Information Agents Workshop, CIKM, Baltimore, December 1-2, 1995. <http://www.cs.umbc.edu/~cikm/iiia/submitted/viewing/whutchi.html>
- Hutchison, W. R. (1997a, May). *Designing an operant organism, an operant theoretical system*. Paper presented at the annual meeting of the Association for Behavior Analysis, Chicago.
- Hutchison, W. R. (1997b). *The 7G operant behavior toolkit* (software and documentation). Boulder, CO: Behavior Systems.
- Hutchison, W. R. (1997c). We also need complete behavioral models. *Journal of the Experimental Analysis of Behavior*, 67, 224-228.
- Oah, S., & Dickinson, A. M. (1989). A review of empirical studies of verbal behavior. *The Analysis of Verbal Behavior*, 7, 53-68.
- Skinner, B. F. (1957). *Verbal behavior*. New York: Appleton-Century-Crofts.
- Skinner, B. F. (1969). *Contingencies of reinforcement*. New York: Appleton-Century-Crofts.
- Stephens, K. R. (1996, May). *Behavior analysis, verbal behavior, and intelligent agents*. Paper presented at the annual meeting of the Association for Behavior Analysis, San Francisco.
- Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: An introduction*. Cambridge, MA: MIT Press.
- Vihman, M. M. (1996). *Phonological development: The origins of language in the child*. Cambridge, MA: Blackwell.