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IMPROVING ON SKINNER: AN EVOLUTIONARY THEORY OF BEHAVIOR DYNAMICS AND ITS NEURAL INTERPRETATION

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Smith argues that Skinner's selectionist explanation of behavior is limited by its inability to account for the first instance of a behavior that is qualitatively different from behaviors that currently exist in an organism's repertoire. This may not be the only problem with Skinner's selectionist account, however, and in fact it may not be the most serious one. A significant element missing from the account is a causal mechanism that explains how behavioral selection occurs at all. *That* selection occurs is not in doubt, for reinforced behaviors in fact are observed to survive and become more plentiful in an organism's repertoire. But a causal mechanism that makes selection happen does not appear in Skinner's theory. Interestingly, this same failing plagued Darwin's theory of natural selection, and led to significant criticism of it, until Mendelian genetics was rediscovered and provided the causal explanation that was missing (Mayr, 1982; Tryon, 2002).

It will be argued here that the missing mechanism in Skinner's selectionist account can be supplied by an evolutionary theory of behavior dynamics and its neural interpretation (McDowell, 2013a). As will be explained, this mechanism also solves the problem of the first instance of qualitatively distinct behaviors. The evolutionary theory does not replace Skinner's theory of selection by consequences; rather, it augments his theory, just as Mendelian genetics augmented Darwin's theory of natural selection.

The Evolutionary Theory

The evolutionary theory is a complexity theory, which means that it is stated in the form of simple, low-level rules, the joint operation of which generates higher-order emergent outcomes that can be compared to data. Complexity theories are a modern alternative to traditional theories in science, which are often stated in the form of differential equations that describe straightforward cause and effect (Wolfram, 2002). Newton's second law of motion, for example, states that a force applied to a body causes it to accelerate, and that the magnitude of the acceleration is directly proportional to the applied force and inversely proportional to the body's mass. A rather different natural phenomenon is the behavior of a flock, or murmuration, of starlings. The flock takes on various elaborate, constantly changing shapes as it moves through the air (see Bunyard-Wild, 2013, for a video). These dynamic changes are not likely to be caused by external forces. Instead, they are more likely to be the result of each bird following simple rules, such as "don't collide with other birds" and "stay with the flock" (Ballerini et al., 2008). The constantly changing shape of the flock is an emergent outcome of the birds following these rules. Importantly, an emergent outcome like this cannot be predicted by examining the rules that produce it, or by manipulating

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them mathematically. Instead, the rules must be allowed to operate repeatedly over time in order to reveal the emergent outcome. A system that works in this way is called a complex system.

The evolutionary theory is stated in the form of three low-level rules that operate on a population of potential behaviors. These are Darwinian rules of selection, reproduction, and mutation. Potential behaviors in the theory are instantiated in the form of bit strings, or genotypes, that can recombine by swapping bits, and that can undergo mutation by having a bit in the string flipped. Each bit string can be translated into a decimal integer, which is taken to represent the phenotype of the potential behavior. Populations of potential behaviors can be used to animate artificial organisms (AOs) that may then be placed in any experimental environment. An AO emits one behavior at random from its population of potential behaviors at each tick of time. This produces a steady stream of behavior that can be recorded and studied just as the behavior of a live organism is recorded and studied. If an emitted behavior is reinforced by the environment, then the theory's selection rule operates. The result is that behaviors like the emitted behavior increase in frequency in the population. Following the emission of a behavior and its possible reinforcement, the reproduction rule operates. Pairs of what may be referred to as parent behaviors reproduce by recombination, that is, each parent contributes some of its bits to build a child behavior. Once reproduction is complete, and a new population of potential behaviors has been constructed, the mutation rule operates. According to this rule, a small number of behaviors chosen at random undergo mutation, which is carried out by flipping a random bit in the behavior's bit string. Reproduction by recombination, and mutation, may increase the variability of the behaviors in the population. The repeated operation of the theory's three rules causes the population of potential behaviors to evolve under the selection pressure of consequences from the environment. Note that both reproduction by recombination, and mutation, can produce novel behaviors that are not present in an existing population.

The evolutionary theory can be tested by comparing the behavior of AOs animated by the theory to the behavior of live organisms. Since the theory was first proposed in 2004, it has been tested extensively and has been found to generate behavior in a wide variety of experimental environments that is indistinguishable, both qualitatively and quantitatively, from the behavior of live organisms (e.g., McDowell, 2013a, 2019).

Neural Interpretation of the Evolutionary Theory

But how is the evolutionary theory related to material reality? After all, behaviors are not bit strings, they do not reproduce, and they do not undergo mutation. Staddon and Bueno (1991) provide a pathway toward answering this question: "…if our…theory really works well as an explanation for behavioral data, it must reflect something true about the neural processes that underlie those data" (p. 6). Does the brain operate as a selectionist system, then? Many authors have suggested that it does (e.g., Edelman, 1978, 1987; Hayek, 1952a, 1952b; McDowell, 2010; Pringle, 1951). Hence, one way the evolutionary theory might be related to neural functioning is that elements of the theory may map directly onto material processes in the brain. For example, Fernando et al. (2012) discussed a number of neural mechanisms that might implement selection, including Seung's (2003) hedonistic synapse. This synapse strengthens when neural firing is followed by reward and weakens when neural firing is not followed by reward, or is followed by punishment. Seung's hedonistic synapse was initially a hypothetical construct, but has since been found in the brain (Gerstner et al., 2018). Regarding reproduction, Fernando et al. (2008) demonstrated that neural circuits can reproduce by recombining neurons in 3-dimensional volumes of brain tissue, thus mirroring the recombination that occurs in the evolutionary theory. Regarding mutation, Popa and McDowell (2016) suggested that this process might be implemented by spontaneous fluctuations in the brain's default mode network. Another possible neural implementation of mutation is the regulation by midbrain dopamine of jumps between attractor states in cortico-striatal loops (Costa, 2011). The different attractor states correspond to different, possibly novel, behaviors. As evidence for this hypothesis, Costa *et al.* (2006) showed that in mice, increased striatal dopamine levels led to more variability in behavior, while depleted dopamine levels caused an absence of novel behavior. Increased striatal dopamine is negatively correlated with the level of synchrony in striatal neurons; less synchrony causes more jumps between attractor states in cortico-striatal loops, and consequently more novel behaviors. Yet another possible neural implementation of mutation entails tonically active neurons (TANs) in the basal ganglia. These neurons act as modulators of randomness in behavioral output; the more active they are, the greater the variability in behavior (Granger, 2006). In a recent implementation of punishment in the evolutionary theory, the strength of punishment-induced mutation is modulated by the context of reinforcement in which it occurs; the richer the context, the weaker the effect of the punishment-induced mutation (McDowell & Klapes, 2019). TANs may exhibit a similar property. Their activity is inhibited by striosomes, which are active in the presence of large rewards (Granger, 2006). In other words, the effects of mutation are lessened in a richer reinforcement context. This modulation of neural activity by the context of reinforcement is consistent not only with the theory's implementation of punishment-induced mutation, but also with the general effect of mutation in the theory. The richer the reinforcement context, the lesser the effect of any type of mutation on the population of potential behaviors.

This realist interpretation of the evolutionary theory is appealing and worth pursuing. However, it may be that the biochemical and physiological operation of the brain is too complicated to permit a completely satisfying account of selectionist functioning in physical terms. Various authors have made a similar argument about artificial neural networks as models of the brain, specifically, that the material functioning of the brain may be too complicated to model realistically by these networks (Kehoe, 1989; Marr, 1997, 2000; McDowell, 2013a). It is also possible that parallel selectionist algorithms operate at different scales (Fernando et al., 2012) in the evolutionary theory and in the brain, thus making a comparison between the two problematic.

An alternative to material realism as a neural interpretation of the evolutionary theory is what has been referred to as supervenient realism (McDowell, 2017). This perspective acknowledges that the operations of the brain and the operations of the evolutionary theory are different. The former are biochemical and physiological; the latter are symbolic and algorithmic. But if the two sets of operations give the same answer, that is, if they generate the same behavioral output, then they must be *functionally* equivalent. In that case, the algorithmic operation of the theory can be said to supervene on the material functioning of the brain. Put another way, the evolutionary theory is a way of explaining how the brain works. According to this perspective, it does not matter whether physical mechanisms of selection, reproduction, and mutation can be found in nervous system functioning. Whatever the material operations of the brain may be, they are functionally equivalent to the algorithmic operations of the evolutionary theory, given that the nervous system and the theory generate the same behavioral outputs. On this view, selection, reproduction, and mutation as implemented in the theory are emergent properties of nervous system functioning.

A simple example of supervenience and emergence may be instructive. Consider an individual who takes three jars from a cupboard, counts 15 beans into each jar, pours the beans out onto a table, and then counts them, obtaining a total of 45 (cf. Feynman, 1985/2006). The material operation of this system entails only physical movements and counting, but it carries out the formal multiplication, 15×3. Formal multiplication entails lining up the numbers, consulting a multiplication table, and following the procedures of arithmetic taught in elementary school. One may say that the multiplication supervenes on the material operation of the beans-and-jars system, or alternatively, that the multiplication is an emergent property of the system's operation. Note that the formal multiplication constitutes a functional theory of how the material system operates. If the number of beans-per-jar, b, and the number of jars, j, are known in advance, then the theory can calculate the results of the system's operation by the formal multiplication, bj, even though no such multiplication is actually carried out by the system. Put another way, the beans-and-jars system behaves *as if* it were carrying out the formal multiplication. Note that what is realist in this theory is not the physical operation of the system (which the theory does not address), but the multiplication that supervenes on this operation. Hence the theory is an instance, not of material, but of supervenient, realism. Analogously, asserting that the evolutionary theory supervenes on brain functioning, is to assert that the brain operates *as if* it were carrying out the processes of selection, reproduction, and mutation, even though those processes may not be identifiable in the material operation of the brain.

Metaphysics

In the final section of his article, Smith discusses differences between the (quantitative or materialist) metaphysics of a behavioral analysis, and the (qualitative or nonmaterialist) metaphysics of a cognitive analysis. He suggests that the correct metaphysics can only be identified by research that successfully leads to empirical generalizations. Hence, according to Smith, there is a tension between behavioral and cognitive analyses that could conceivably be resolved in some way.

An alternative to Smith's view (McDowell, 1991) acknowledges the difference in metaphysics, but notes that the empiricist epistemology entailed by both types of analyses, when combined with their different metaphysical perspectives, leads to different types of statements about the world. For example, the truth or falsity of propositions based on a quantitative metaphysics can be decided with certainty by applying an empiricist epistemology. Consider the proposition that contingent timeout suppresses behavior. Recording the frequency of behavior after timeout has been applied will answer this question definitively. Either the response count decreased, or it did not. On the other hand, empirical results obtained from the study of a proposition based on a qualitative metaphysics can only form a basis *for arguing* that the proposition is true or false. This is because the empiricist epistemology does not, and cannot, make direct contact with the nonmaterial elements of the proposition. Consider, for example, the proposition that a therapy client has an authoritarian personality. This may be studied empirically by administering assessment instruments, but the results of this assessment are not directly connected to the client's personality, however that might exist in the world. The results of the assessment may be empirically related to the results of other assessments (Campbell & Fiske, 1959), but they are only indicative of, or constitute a handle on, the personality itself. Another psychologist might assert that the authoritarian personality indicated by the assessment is really a defense mechanism, and that the client in fact is dependent and submissive. Questionnaires and Rorschach tests might be administered to test this secondary proposition, but again, a decisive answer cannot be obtained. The results can only form a basis for arguing that the client's personality is submissive rather than authoritarian.

According to this view, the different metaphysical perspectives of behavioral and cognitive analyses make it unlikely that they can be reconciled. Because the world is constituted differently for the two types of analyses, it may be best to consider them different disciplines, as has been suggested by others (e.g., Epstein, 1985; Fraley & Vargas, 1986). On this view, there is no tension between behavioral and cognitive analyses, in the sense that they might be reconciled in some way. On the contrary, they entail different conceptions of the world. The same empiricist epistemology applied to different metaphysical perspectives produces different kinds of statements about the different worlds.

Conclusion

The evolutionary theory supplies a causal mechanism for Skinner's account of selection by consequences, specifically, the evolutionary dynamics carried out by the theory's rules of selection, reproduction, and mutation. This causal mechanism may be identifiable in the material operation of the brain, or it may supervene on brain functioning. In either case, it explains how Skinner's selection by consequences works.

The evolutionary theory also solves the problem of the first instance of a behavior that is qualitatively different from existing behaviors in an organism's repertoire. Reproduction by recombination and mutation can both generate novel behaviors, including syntactically novel utterances. Smith himself notes that mutation can change the traits that are available to be selected. It follows that if a purely behavioral account includes a mutation mechanism, and accurately describes behavior (both of which are true of the evolutionary theory), then the production of novel behaviors is consistent with a purely behavioral view. Cognitive models are not required.

Finally, it might be best to consider behavioral and cognitive analyses, not as competing accounts, but as different disciplines with different subject matters.

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