

Andrei Popa Research Statement

How does behavior change over time, throughout an individual's lifetime?

As children, our ability to act on our environments is limited. Over time, behavioral repertoires become rich, nuanced, and effective: new behaviors are learned, some fade away, while others become highly contextual. The basic principles that underlie these changes, that is, the dynamics of adaptive behavior, are yet to be understood.

I approach this question from two, converging directions. I use computational modelling to implement dynamic theories of behavior change. In parallel, I use human laboratory studies to explore the fine-grained structure and temporal organization of adaptive behavior and to verify computational findings.

Behavioral repertoires as Complex Systems

One of the more successful accounts (for an overview, see McDowell, 2013b) was inspired by the analogy between learning and biological evolution (Pringle, 1951). The basic idea is straightforward: it proposes that, much like the phenotypes in a biopopulation, behavioral repertoires are shaped by low-level processes of *selection* and *variation*. These processes operate locally, *here-and-now*, and allow organisms to adapt in dynamic environments. Over time, they produce behavioral structures and properties that cannot be predicted, *ad principia*, by examining the processes themselves. These high-level properties are called *emergent* and systems that exhibit emergence are referred to as *complex systems* (Holland, 1998; also in [NOVA, 2007¹](http://www.pbs.org/wgbh/nova/nature/emergence.html)). Their dynamics can be studied computationally, as discussed in McDowell and Popa (2009): implement the system's parts and processes in an abstract form, allow the system to evolve, and compare the emergent behavior with the behavior of biological organisms.

Computational Darwinism

The computational model discussed here (McDowell, 2004) implements a population of behaviors, positive reinforcement, and low-level rules of *selection*, *recombination*, and *mutation*. Behaviors have “phenotypes” and “genotypes”, represented by integers (e.g., 42) and their corresponding binary form (e.g., 101010). Phenotypes can be separated into target classes, functionally equivalent to pressing levers in an operant chamber. Target behaviors, on occasions, can acquire reinforcers; non-target behaviors are never reinforced.

An experiment begins with a random population (generation 1), equivalent to a naïve, untrained organism; from it, one behavior is chosen at random and emitted. The emission, equivalent to one lever press, triggers the Darwinian cycle, which transforms the existing population into a new one (generation 2). From it, one behavior is emitted, a third generation is created, and so on. Reinforcing events tend to concentrate the next generation around the just-reinforced phenotype. Non-reinforced emissions result in more dispersed, variable populations. The emissions are recorded and analyzed as if they were the behaviors of a biological organism.

PRE-CANDIDACY WORK

Agreement with mathematical descriptors of steady-state behavior

The field of quantitative analysis of behavior generated a wealth of fine-grained knowledge about operant behavior. This includes the “matching equations”, known to describe the overall relation between responses and reinforcers with great accuracy, and across species (for a review, see McDowell, 2013a). These equations were used to assess the behavior generated by

¹ <http://www.pbs.org/wgbh/nova/nature/emergence.html>

the computational model. In McDowell and Popa (2010) we showed that when reinforcement rate varied (constant reinforcer magnitude), choice behavior was described in quantitative detail by Baum's (1974) power function matching equation. In McDowell, Popa, and Calvin (2012) we showed that when both reinforcement rate *and* magnitude varied, choice behavior was well described by the bivariate (or generalized) matching equation (Baum & Rachlin, 1969; reviewed by Cording, McLean, & Grace, 2011). In both cases, the equations explained most of the variance preference patterns ($pVAF > 98\%$) and yielded parameter values for sensitivity to reinforcement rate ($a_r \sim 0.8$) and magnitude ($a_m \sim 0.6$) indistinguishable from those observed in live organisms. These outcomes emerged, unguided, from the reiteration of Darwinian rules, providing support for the evolutionary account of behavior dynamics.

Changeover Delay, in the real world (COD) and in the computational model (COMP_{COD})

The everyday is filled with distractions that can interfere with activities that require sustained effort. One solution is to make switching between activities more difficult. A common practice is to arrange a changeover delay (COD; Findley, 1958): a short interval contingent on switching behavior, during which all reinforcers are withheld (hence delayed). This is known to decrease the frequency of changeovers and increase sensitivity to reinforcement. For my master's project, I showed that a computational variable (Popa & McDowell, 2010; see also Popa, 2013, p. 19-21) is functionally equivalent with the changeover delay (COD) arranged in experiments with living organisms: high values produced fewer changeovers and higher sensitivity to reinforcement (and vice-versa). In this document, I denote this variable with COMP_{COD} (computational COD).

DISSERTATION

1. *Mutation rate*, environmental characteristics, and maladaptive behavioral variability

In the model, each emission, or response, triggers a Darwinian cycle. After *selection* and *recombination* create a new population, it is affected by *mutation*: a certain percent of behaviors, referred to as *mutation rate*, is randomly selected and "mutated": one bit in its "genotype", chosen at random, is "flipped" from 1 to 0 or 0 to 1. Previous work, some of which was presented at ABAI (2011), suggested that high mutation rates may produce behavioral characteristics that could be described as *impulsive*. The first specific aim of my dissertation project was to explore the effects of various mutation rates, under different environmental conditions, on variability and organization of choice behavior.

High mutation rates produced severely disorganized behavior, strikingly similar to those observed in ADHD-diagnosed children: *"...decreased sensitivity to reward, switched more often between activities, engaged less often in continuous-responding, abandoned the task faster, took longer to re-engage, acquired fewer resources, exhibited high levels of topographic variability..."* (from Popa, 2013, p. 42). Similar to the behavioral symptoms observed in ADHD, the disorganized behavior produced by high mutation rates were counteracted in "good environ" and worsened in "bad" environs (p. 43-46).

From *mutation rate* to ADHD and brain function

These findings led me to hypothesize that *mutation rate* may be functionally equivalent to the level of spontaneous fluctuations in the brain's default-mode network (DMN; Raichle et. al., 2001), recently shown to be associated with high levels of intra-individual variability (Buckner et. al., 2008; Weissman et. al., 2006) and to interfere with goal-directed activity (ref). This hypothesis can be explored by recording brain activity while the participant is engaged in continuous choice-behavior. The experimental procedure would have to be short enough to be used in conjunction with brain-investigation

technologies (e.g., EEG, ERP, fMRI), but long enough to produce high frequencies of responses and reinforcing events.

2. Verifying model's predictions in a fast-paced, continuous-choice environment

For the second part of my project I programmed and tested a “virtual operant chamber”. I arranged a continuous-choice environ in which five concurrent schedules, each in effect for only 200 seconds, scheduled very high reinforcement rates (e.g., 100 reinforcers/minute). One group of students experienced a 2-seconds changeover delay (COD_2s); the second group did not (No_COD). Their choice behavior was compared along the same eight behavioral dimensions used to explore behavioral variability in the computational model.

When a two-second COD was contingent on switching, behavioral variability noticeably lower than in the No_COD condition. This provided further support for the equivalence between COMP_{COD} and COD and showed that computational models can be used to predict human behavior (Popa, 2013, p. 59 - 60). Furthermore, behavior was relatively well described by the power function matching equation (COD_2s; $a \sim 0.7$, $b \sim 1.0$, pVAF $\sim 75\%$), despite the short experimental duration and very high reinforcement rates.

From computational models to brain function, via fast-paced procedures

My findings, unique at the time of their publication, suggest that fast-paced procedures can be used to explore equivalences between computational variables and properties of the nervous system. For example, if *mutation rate* and the level of spontaneous fluctuations in the brain's default mode network (DMN) are functionally equivalent, then choice-behavior that correlates with high levels of DMN fluctuations should match that produced by high mutation rates, as discussed in Popa & McDowell (2016).

CURRENT WORK AND FUTURE DIRECTIONS

Currently, I am developing an evolutionary model that, in addition to *selection events* (positive reinforcement), implements *elimination events* and *contextual cues*. The first step is to test the current implementation in single- and concurrent-schedule environments, by comparing its outcomes against known mathematical descriptors. Preliminary studies on choice behavior showed good conformance with the power-function matching equation ($a \sim 0.8$; $b \sim 1.0$; pVAF $> 98\%$). Next, I will verify if elimination events (negative selection) have punishing effects and if contextual cues become discriminative stimuli. As verification criteria, I will use existing findings, such as Bradshaw's et al. results on the effects of response cost in single-schedules (1978) and predictions made by quantitative models of punishment (e.g., de Villiers, 1980).

In parallel, I will use the human research program to expand our knowledge on the effects of discriminative stimuli and avoidance/escape behavior. Recent work, conducted in collaboration with my former students (see Vitae for a complete list), has produced results that can further inform and verify computational developments. For example, we investigated human behavior in concurrent schedules, with signaled and unsignaled (invisible) target classes (with Tang, X.). The outcomes of these experiments can be compared to behavior generated by the model in the presence or absence of *contextual cues*. In other studies, we explored the effects of extinction on positively reinforced behavior (with Forbes, A.) and on negatively reinforced behavior (Popa & Grissom, 2017), results that can be further used to verify the new computational implementation.

Social Interactions as “behavioral Turing tests” for the evolutionary model

Both the model and the human experimental procedure can be expanded to the study of social interactions. In the model this can be done by instantiating multiple populations of behaviors and allowing them to evolve entangled, each emission being both behavior and consequence (for others). Similarly, the human procedure can be expanded to “multiplayer mode” (so to speak). Bridging the two will allow humans to interact with other humans *and/or* with digital agents. Will they recognize the difference between human and computer by behavior alone? Will they cooperate? Compete? Avoid each other? Will in-groups and out-groups spontaneously emerge?

STUDENT INVOLVEMENT AND FUNDING POTENTIAL

This research program has sparked students’ interest and offers excellent learning opportunities to aspiring researchers. For example, learning about computational modelling and complexity science in general is intellectually rewarding and entails the acquisition of generally-useful computer skills. Similarly, verifying computational predictions in experiments with human participants (or vice-versa) contributes to the development of computational thinking and complex reasoning and offers a rare opportunity to explore the connections between the natural and digital world. As an educational platform, it has a good potential to attract funding aimed to engage students in research (e.g., Research Experiences for Undergraduates; an NSF initiative). As a research enterprise, this work is congruent with the interests of agencies that fund basic science projects on adaptive learning and translational science with clinical, educational, or otherwise social relevance, such as DARPA, NIMH, or NSF. Considering the increased interest in artificial intelligence shown by private organizations (e.g., Google®, OpenAI®, etc.), is likely that its funding potential will continue to increase.

SIGNIFICANCE

The question that drives my research, *how behavior changes over time*, is directly relevant to all phenomena in which adaptive behavior plays a significant role, from child rearing and personality development, to global warming and artificial intelligence. My approach is inherently transdisciplinary, combining theoretical developments and experimental techniques from experimental analysis of behavior, computer science, developmental psychology, cognitive-neuroscience, evolutionary biology, and information theory. Building upon ideas from these domains, I seek to make fundamental contributions to our understanding of the basic principles that underlie moment-to-moment changes in voluntary action, cognitive processes, and their underlying neuronal activity; in other words, about the emergence of psychodiversity and individuality.