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Fitness landscapes among many options under social influence

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HIGHLIGHTS

- A learning model and fitness-landscape function; agents choose from N options.
- Its three key factors: social learning, transparency of choice, change through time.
- Our hill-climbing algorithm finds expected optimal decisions as landscape peaks.
- Multiple equilibria at each point on landscape, which is rugged even for $N=3$ choices.
- Initial conditions, path dependence underlie optimal behavior among social organisms.

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ABSTRACT

Cultural learning represents a novel problem in that an optimal decision depends not only on intrinsic utility of the decision/behavior but also on transparency of costs and benefits, the degree of social versus individual learning, and the relative popularity of each possible choice in a population. In terms of a fitness-landscape function, this recursive relationship means that multiple equilibria can exist. Here we use discrete-choice theory to construct a fitness-landscape function for a bi-axial decision-making map that plots the magnitude of social influence in the learning process against the costs and payoffs of decisions. Specifically, we use econometric and statistical methods to estimate not only the fitness function but also movements along the map axes. To search for these equilibria, we employ a hill-climbing algorithm that leads to the expected values of optimal decisions, which we define as peaks on the fitness landscape. We illustrate how estimation of a measure of transparency, a measure of social influence, and the associated fitness landscape can be accomplished using panel data sets.

1. Introduction

Imagine a human decision scenario, modern or ancient, such as a person choosing a cereal at a grocery store or a prehistoric forager deciding which stand of trees to visit to gather hazelnuts. We tend to think of the former as economics and the latter as human ecology, but in each case, the decision has many similar options and depends on (1) the transparency of how good each option is, (2) the intrinsic utility of each option, and (3) the social utility of each option.

As researchers, we can observe the proportion of individuals who choose each option and, based on that information, attempt to infer these three quantities. Leaving social utility aside for a moment, consider just transparency and intrinsic utility. We expect that if the intrinsic utility of each choice is highly transparent, then the probability distribution of decisions is in good accord with the fitness landscape, and there will be a single peak at the highest-utility option. As transparency decreases, the probability distribution flattens out as the fitness landscape becomes less visible and utility differences can no longer be discerned among the different options. At zero visibility, the probability distribution approaches a uniform distribution, and we effectively have random choice.

Now add back in social utility. For example, a shopper chooses the brand that he just saw someone else choose, or perhaps a forager follows her kinfolk to a particular stand of trees. Then aggregate those decisions over time and/or people. With social utility added to the mix, herding effects are possible, and the most popular option among the aggregated observations need not have

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the highest utility. Indeed, if social utility is high and intrinsic transparency low, the respective distributions of choice probability and intrinsic utility among the options could differ significantly.

This exemplifies the complexity of modeling a fitness landscape of discrete choice under social influence. Here we build on previous work by examining cases where there may be multiple observed distributions of choices for transparency, utility, and social influence. We sketch an approach to estimation of the fitness landscape in the presence of multiple equilibria. This approach builds on a two-dimensional map we recently presented to track decision making as it relates to learning and transparency (Bentley et al., 2014; Brock et al., 2014).

To place our study in a broader context, we summarize below some of the recent work that has been done in the area of cultural learning, given that it forms the foundation of the horizontal axis of our map. We stress that the econometric studies we borrow from do not deal with the actual estimation of fitness functions, nor do they deal with the computation of equilibria or provide a theory of *which* equilibria are likely to be observed when actual estimation is conducted in the presence of multiple equilibria. Addressing these issues represents our contribution to the formulation of fitness functions and their estimation. We necessarily use terms such as "transparency," "social conformity," and "social interactions," which are subject to the imprecision of words in contrast to the precision of the mathematical concepts for these terms that we develop later.

2. Social influence: a key element in decision making

When agents are faced with making a decision that involves multiple options, they can do one of two things. They can either learn individually, where they attempt to think things through by themselves, or they can learn socially by using other agents as sources of information. Within any population, the precise mixture of individual, or independent (asocial), learners versus social learners—a dichotomy sometimes referred to as information "producers" versus information "scroungers" (Mesoudi, 2008; Rendell et al., 2011)—may be crucial to a group's ability to climb a rugged fitness landscape (Rogers, 1995; Mesoudi and Whiten, 2008; Rendell et al., 2010; O'Brien and Bentley, 2011; O'Brien et al., in press). The reason for this is that whereas social learning spreads behaviors, it depends on individual learning to generate them in the first place. The question is, how does an agent integrate social and individual learning (Perreault et al., 2012), and how do their collective decisions affect fitness? Several studies have examined this question (e.g., Giraldeau et al., 2002; Kendal et al., 2009), many building on the work of Rogers (1988), who proposed that environmental change lowers group fitness when social learners copy outdated environmental information (Enquist et al., 2007; Rendell et al., 2011; Rieucau and Giraldeau, 2011). If the environment does not change, group fitness tends to increase as social learners copy optimal behaviors. Similarly, natural selection favors agents who place heavy weight on social cues when the environment changes slowly or when its state cannot be well predicted using individual learning (Perreault et al., 2012).

A population will ideally contain an optimally adaptive mix of the two learning strategies, but there is no assurance that this optimal mix will occur, as other steady-state mixes might exist. Numerous studies suggest that about 5% of informed individuals are enough to guide a social group (e.g., schooling fish) to a destination (Dyer et al., 2009; Herbert-Read et al., 2013; Wolf et al., 2013; Kurvers et al., 2014). Among that minority, this "pied piper" effect is augmented by intensity of direction (Couzin et al., 2011), which we might generalize as the "intensity of choice" (Bentley et al., 2014), or the accumulation of knowledge (Gomes, 2006).

In traditional human societies, social learning is usually transparent, as experts in different essential categories of adaptive knowledge (medicinal plants, hunting, fishing, cultivation) are well known to the group members (Henrich and Broesch, 2011). Over generations, well-directed social learning increases collective knowledge—teachers to students, parents to children, experts to general communities. As a consequence, the benefits of social learning are substantial enough for it to have been a key factor in human evolution (Hruschka, 2010; Hoppitt and Laland, 2013; Christakis and Fowler, 2014). Small groups can outperform even the most skilled/knowledgeable individual on complex tasks (Woolley et al., 2010) and in remembering information (Clément et al., 2013).

Transparency is not assured, however. Even among social animals, if misinformation invades the social-learning process, it can spread (Couzin et al., 2005). As information spreads between, say, Facebook or Twitter friends (Aral et al., 2009; Bond et al., 2012; Garcia-Herranz et al., 2014), expertise is not necessarily transparent to all members of the networks. In cases where expertise is not transparent, a good strategy might be to copy recent success (Laland, 2004; Rendell et al., 2010). Schools and flocks may be seen as "copying the recent": when flocking agents are copying their neighbors' current direction of travel, the information is available practically instantaneously (Couzin et al., 2005).

An empirical challenge is in characterizing social-learning strategies from data aggregated at a broader scale than individual-agent motivations. For example, social-psychology experiments (e.g., Salganik et al., 2006; Lorenz et al., 2011) show that providing information about what others are doing often reduces the diversity of independent judgments within trials but increases variance between trials, thereby reducing the predictability and accuracy of the aggregated mean of those judgments.

Social influence is best recorded by close observation of each agent and its interactions through time (Hobaiter et al., 2014). If the observational data are more aggregated, however, it is difficult to demonstrate social learning without resorting to strong a priori assumptions (Shalizi and Thomas, 2011; Thomas, 2013). These sorts of aggregated datasets are common, but can they be used to distinguish between genuine social influence and individual discovery? The "three-degrees-of-influence" hypothesis concerning behaviors that spread within human social networks beyond one's immediate friends (Christakis and Fowler, 2013) can also be explained by simple autocorrelation through individual discovery combined with homophily—the tendency for individuals with similar traits to co-associate (Brock and Durlauf, 2001; Aral et al., 2009; Thomas, 2013). We return to the issue of homophily later.

3. A bi-directional map of decision making

Following our discussion above, we focus on two important factors, or "dimensions," in terms of how decisions are made in the face of multiple options: the magnitude of social influence in the learning process and the transparency of costs and payoffs to either social learning or individual learning. These two dimensions, together with how they change over time, are the essence of discrete-choice theory with social influence (Brock and Durlauf, 2001; Brock et al., 2014). We chose discrete-choice theory as an exploratory vehicle because of its relationship to other theories of decision making, both individually and in groups, such as replicator dynamics and Bayesian updating and information theory (Krakauer, 2011) and statistical mechanics (Durlauf, 1999).

This led us to propose a theoretical framework grounded in a bi-axial map that extracts, from observational data, the transparency of decisions and the extent to which a behavior is acquired socially versus individually (Fig. 1) (Bentley et al., 2011a, 2011b,