PREREGISTRATION

SOCIAL LEARNING IN EXPERIENCE-STRUCTURED GROUPS

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Summary

Most models and experiments of social learning omit age structure and study strategic learning in fixed groups with everyone having equal levels of experience. Here, we introduce a "microsociety" experiment where experience structure is simulated through a simple schedule of migration and environmental change. We provide an outline of the proposed study, simulate experimental data from a mathematical learning model and develop a statistical framework to analyze strategic learning in such an experience-structured informational environment with spatial and temporal variability.

Background

Cultural evolution is partly driven by the strategies individuals employ to learn behavior from others (Boyd & Richerson, 1988; Laland, 2004; Kendal et al., 2018). Both formal models and controlled laboratory experiments have established how humans (and other animals) combine individual and social information strategically to acquire locally adaptive information. Previous experiments that investigated strategic learning let fixed groups of individuals engage in repeated rounds of a learning task and analyzed how individuals' choices are affected by the payoffs they received and the choices of other members of their group. Typical findings are that social learning is generally adaptive but underused (McElreath et al., 2005, 2008), that individuals tend to use a combination of payoff-biased, frequency-dependent and a set of other strategies (Morgan, Rendell, Ehn, Hoppitt, & Laland, 2011; McElreath et al., 2008), that social learning strategies can regulate the "wisdom" of collective decision making (Toyokawa, Whalen, & Laland, 2019) and, finally, that there are considerable inter-individual differences in the reliance on social information (Efferson, Lalive, Richerson, McElreath, & Lubell, 2008).

While group membership in most lab experiments is fixed with participants always having the same level of experience in their current environment, natural populations are characterized by overlapping generations and experience structure. Infants grow up in an informational environment where potential social models are characterized by different ages and,

Date: 15/07/2019; note this document is work in progress and gets updated as the project develops.

thereby, different levels of experience. Whether copying older rather than younger individuals is adaptive is not straightforward, but depends on the relative strength of different interacting forces. These forces include the importance of a cultural trait for survival, the difficulty to acquire the trait as a juvenile and the rate of environmental change (Deffner & McElreath, in preparation).

Moreover, birth and death are not the only processes that result in such an experience gradient among demonstrators, organisms often also migrate into new environments during their lifetimes, which similarly results in a population where group members are characterized by different levels of experience in the present environment. To better understand the adaptive logic of social learning in real organisms, we must not only study learning processes in isolation but investigate how learning intersects with demography and operates in dynamic groups with varying experiences.

Individuals migrating into new environments have to adopt locally specific adaptive knowledge. Formal modeling has explored the consequences of such spatial variability as compared to temporally varying environments that change for everyone at the same time (Nakahashi, Wakano, & Henrich, 2012). One important finding is that conformist learning is generally adaptive in spatially varying environments, but not so much in temporally varying environments. Conformity lets learners filter out the non-adaptive variation brought in by migrating individuals and lets migrants themselves acquire locally adaptive behavior very reliably by pooling information across multiple individuals (Nakahashi et al., 2012; Mesoudi, 2018). If the environment changes temporally, in contrast, everyone becomes non-adapted at the same time, such that conformist learning is of less value. Despite its theoretical relevance, this difference in adaptive social learning strategies between spatially and temporally varying environments, has not been investigated empirically.

In sum, we aim to investigate the dynamics of strategic social learning in experience-structured groups that include both spatial and temporal variability.

Experimental Design

Here, we introduce a “microsociety” social learning experiment, in which experience structure is simulated through a simple migration schedule. Such microsociety experiments create social contexts in which groups of individuals can evolve behavioural traditions, through a combination of individual exploration of the environment and the available social information (Schotter & Sopher, 2003; Baum, Richerson, Efferson, & Paciotti, 2004). Unlike many other experimental studies, social information in the present study arises endogenously from the behavior of others in a group. This is important, because in order to uncover the design features of social learning strategies, we must study their use in an informational environment they themselves create. Figure 1 shows the basic experimental setup. Two groups of four individuals engage in 100 rounds of a four-armed bandit task. Circles represent different individuals each characterized by a unique ID. Every 5 rounds, one individual from the first group switches group with a fixed individual from the second group indicated by the white circles: Individual 1, for instance, always switches with individual 5, individual 2 with individual 6, and so on. After 15 rounds, this migration dynamic creates a situation in which each individual in a group is characterized by a distinct level of experience in the current group. Groups have completely switched after 20 rounds and returned back to their original composition after 40 rounds.

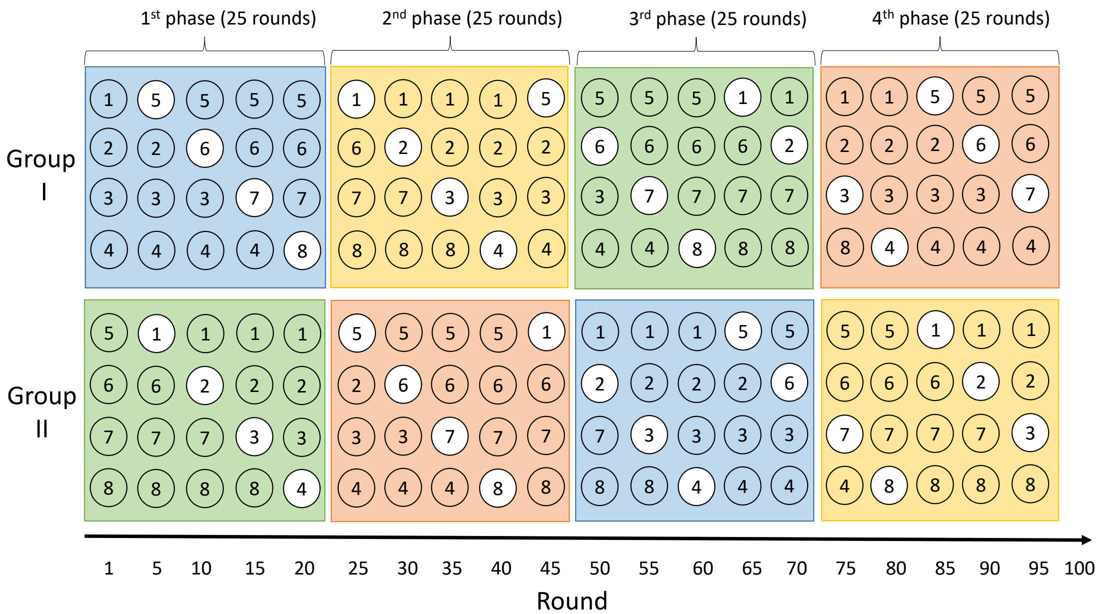

Figure 1. Group Dynamics and migration schedule. Circles represent participants identified by a unique number. Both groups consist of 4 individuals. Every 5 rounds, two individuals (white circles) switch their groups and enter a different group. The colors of the boxes represent the 4 different crop options and indicate which crop is optimal in both groups for a given phase. While the specific crops are randomly selected for each session, the general schedule follows the depicted pattern for all sessions.

During each round, participants have to decide to plant either one of four different crops ("Wheat", "Potatoes", "Corn", "Rice"). Payoffs for all options i are randomly drawn from a normal distribution $\mathcal{N}(\mu_i, \sigma)$, so that payoffs vary among rounds but each option is characterized by a given expected value μ_i. At each point in time, one option has a higher expected payoff than the other three options and participants' task is to find the highest-paying option in order to maximize their payoff. The height of payoffs varies among the 4 phases of the experiment but the difference between the means is always 3 points. We compare a high task uncertainty condition in which the payoff distributions are greatly overlapping ($\sigma = 3$) to a low task uncertainty condition in which there is little overlap ($\sigma = 1.5$).

After the first round, participants can access information about their individual payoff from the previous round (i.e. private information) as well as the crop choices of the other group members from the previous round (i.e. social information). Additionally, participants can obtain information about how many rounds a given individual (including themselves) has already spent in the current group. Figure 2 shows a screenshot of the experimental display. The background color (green vs. blue) indicates which group an individual is currently in. All information is hidden at first and individuals must hover over the boxes to see the respective information. Recording how long individuals hover over each box, we can not only study how participants sample different sources of information but also have complete data about the informational environment that resulted in a given behavioral choice.

The experiment is divided into 4 phases of 25 rounds each. Which option yields the highest

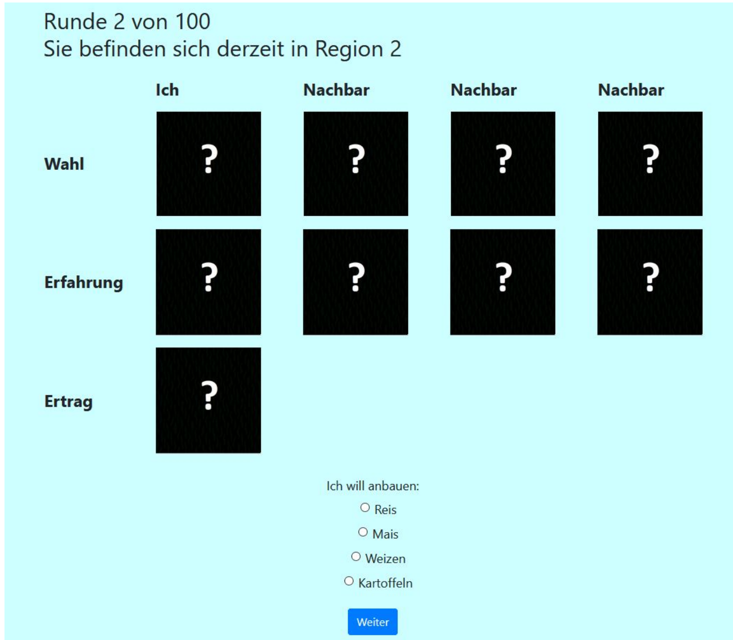

Figure 2. Exemplary screenshot of experimental display.

average payoff in each phase (indicated by color in Fig. 1) is randomly determined for both groups but in a way to ensure that different crops are optimal in both groups. Therefore, migrating individual always have to re-learn which crop yields the highest payoff in the present environment. In combination with the migration schedule described above, these changes in the environment create a dynamic through which participants -over the course of the experiment- enter new groups at different times relative to the last switch in the environment.

We aim to investigate how individuals strategically combine private and social information in this sort of experience-structured informational environment that is characteristic of most real organisms. One question is whether individuals prefer to copy more or less experienced individuals and how that changes over time. We are particularly interested in how individuals learn when they enter a new group and how their behavior changes as they become more experienced (dealing with spatial variability). As opposed to that, we will analyze how individuals learn when the environment changes for all at the same time (dealing with temporal variability).

Data Analysis

Experience-weighted attraction (EWA) models

We will analyse these data using Bayesian multilevel experience-weighted attraction (EWA) models (Camerer & Hua Ho, 1999; McElreath et al., 2005; Hoppitt & Laland, 2013). EWA models are a class of models that link individual (reinforcement-based) updating rules and social information use to population-level cultural dynamics. By fitting real mathematical models of learning as statistical models, these models let us not only investigate the strategies different individuals use to learn from others, but also examine the consequences these choices have for group-level dynamics.

There are two basic building blocks to each EWA model: First, we have an updating or learning equation that tells us how peoples' "attractions" to different behavioral options $A_{i,t+1}$ (i.e. how preferable option i is to the actor at time $t+1$) change over time as a function of previous attractions $A_{i,t}$ and recently experienced payoffs $\pi_{i,t}$. The parameter ϕ describes the weight of recent experience. The higher the value of ϕ, the faster do learners update their attractions in light of new experiences.

$$A_{i,t+1} = (1-\phi)A_{i,t} + \phi\pi_{i,t} \tag{1}$$

The second major part of an EWA model expresses the probability an individual chooses option i in the next round, $t+1$, based on a series of cues available to them. We can divide those cues into asocial (P_A) and social cues (P_S) and the model lets us estimate to what extent an actor's choices were influenced by personal information about the different behavioral options $(1-\sigma)$ and the choices of other group members (σ).

$$P(i|A_{i,t},\theta)_{t+1} = (1-\sigma)P_{A,t+1} + \sigma P_{S,t+1} \tag{2}$$

The asocial choice probability P_A is determined by a multinomial-logistic or *softmax* choice rule which translates the attraction towards option i into the probability this option is chosen next:

$$P_{A,i,t+1} = \frac{\exp(\lambda A_{i,t})}{\sum\limits_{i=1}^{4}\exp(\lambda A_{i,t})} \tag{3}$$

The parameter λ controls how sensitive choices are to differences in attraction scores. As λ is getting larger, choices become more deterministic with the largest attraction score being nearly always selected. As λ goes to 0, choices become noisier which is why λ can also be interpreted as the exploration rate of an individual.

Individuals in the experiment have access to different sorts of social information. Our model estimates the relative influence of frequency-dependent and experience-directed learning as a convex combination of both cues with parameter κ giving the relative influence of experience cues relative to frequency cues.

$$P_{S,i,t+1} = (1-\kappa)\frac{n_{i,t}^{f}}{\sum\limits_{i=1}^{4} n_{i,t}^{f}} + \kappa\frac{\bar{E}_{i,t}}{\sum\limits_{i=1}^{4}\bar{E}_{i,t}}, \tag{4}$$

Conformity exponent f determines how strongly learning is biased towards the majority. When $f = 1$, learning is unbiased; as f becomes larger, individuals become more and more likely to copy the majority. When $0 < f < 1$, individuals are disproportionately copying the minority option. $\bar{E}_{i,t}$ is the weighted average experience of all individuals who chose option i at time t and is calculated as follows:

$$\bar{E}_{i,t} = \sum_{j=1}^{n_{i,t}}\exp(\beta E_{j,t}) \tag{5}$$

Parameter β gives the strength and direction of experience bias. When $\beta = 0$, individuals are indiscriminate with respect to experience in the current region. Negative values of β

Table 1. Summary of model parameters

Parameter	Values	Description
λ	> 0	Influence of attraction on choice; as $\lambda \to 0$ choice becomes noisier
ϕ	[0,1]	Updating rate/weight of recent choices
σ	[0,1]	Social learning weight; relative influence of social and asocial info
κ	[0,1]	Relative influence of experience and conformity; 1 means all "experience-biased"
f	> 0	Strength and direction of frequency dependence; 1 means no bias
β	$]-\infty, \infty[$	Strength and direction of experience bias; 0 means no bias

indicate a bias towards less-experienced individuals, positive values a bias towards more-experienced individuals. We validated this way of parameterize the relative influence of both cues by simulating data from different possible parameterizations and seeing whether this model would recover the simulated dynamics (see below).

Making learning dynamic

We are mostly interested in how learning interacts with demography and unfolds over time, so we want temporally dynamic learning parameters on top of person-specific varying effects. That way, all learning parameters can change depending on the level of experience in a given region or the time since the last switch in the environment. Unfortunately, there is no formal cognitive theory that would give us a principled and distinct functional form of how learning parameters are expected to change over time. Therefore, we explored different modelling options that can broadly be categorized into 4 strategies:

(1) First, one could just fit a different intercept for each unique level of experience pooling information across different levels of experience or not (i.e. "random" or "fixed" effects). Without pooling, the model can estimate arbitrarily complex and individual-specific learning patterns. However, this rather descriptive approach requires a large number of parameters and is quite heavily influenced by single choices, so that the model likely overfits the specific characteristics of the sample. Letting the model pool information across different levels of experience reduces the risk of overfitting, but also makes it harder to detect very abrupt changes in learning that might appear straight after migration/environmental change.

(2) The opposite strategy consists in estimating learning parameters as a direct function of the level of experience. That way, one could estimate the general shape of the relationship with a small number of parameters. For instance, we could assume that the weight of social information, σ, declines exponentially over time, with the model estimating the rate of that exponential decline. The major drawback of that approach is that one has to specify the hypothesized functional form in advance and the model can only identify learning gradients that are compatible with the functional form one imposed.

(3) Instead of assuming a particular functional form, one can also just assume that learning parameters change monotonically over time, i.e. they either constantly decrease or increase as individuals become more experienced. We can construct level of experience as such an ordered categorical predictor for some parameter θ in the following way:

$$\theta_i = \theta_{\text{lowest},i} - (\theta_{\text{lowest},i} - \theta_{\text{highest},i}) \sum_{j=0}^{E_i-1} \delta_j. \tag{6}$$

Each individual is characterized by 2 parameters, $\theta_{\text{lowest},i}$ and $\theta_{\text{highest},i}$, which give their value for the lowest and highest level of experience, respectively. These values determine how strongly θ varies among different experiences for individual i, their difference thus represents the maximum effect of experience on θ. This maximum effect of experience is multiplied by the sum of a number of δ parameters which give the incremental effect of each step in experience (note that all δ_j must sum to one). That way, this model can not only estimate the direction and strength of the experience effect, it can also tell us at which times after migration the largest changes happen.
(4) The last approach we explored consists in modelling the influence of experience on learning using Gaussian process regression, where the model can estimate any arbitrary function. Gaussian processes extend the varying effects approach to continuous categories and allow us to estimate a unique parameter value for each level of experience, while still regarding experience as a continuous dimension in which similar levels of experience result in more similar behavior. Essentially, instead of letting the model estimate the varying effects variance-covariance matrix without constraints from the data, in Gaussian processes we estimate the parameters of a function that expresses how covariance between different levels of experience is expected to change as the distance increases. Specifically, we use the following common kernel:

$$K_{i,j} = \eta^2 \exp(-\rho^2 D_{i,j}^2) + \delta_{i,j}\sigma^2 \tag{7}$$

The covariance between any pair of experiences i and j, $K_{i,j}$, equals the maximum covariance η^2 which is reduced at rate ρ^2 by the squared distance in experience between i and j, $D_{i,j}^2$. There is an additional covariance parameter σ^2 that gets "turned on" by $\delta_{i,j}$ when $i = j$; it expresses the additional covariance for observations with the same level of experience.

Simulations

In order to validate our analytical approach, we conducted agent-based simulations using the exact same setup and parameter values that we will use for the actual experiment with human participants. In each session, we follow 8 simulated participants through 100 rounds of the described experiment and record their choices in a format comparable to the output of the experiment. The behavior of agents is governed by the same mathematical learning rules that we use for the statistical models. The goal was to implement some "extreme" and some more realistic strategies individuals might use and see whether the model would be able to recover the simulated parameter values or at least produce the correct qualitative inferences. In particular, the model should be able to detect sudden switches in learning strategies that might happen right after migration and/or environmental changes.

How to integrate frequency and experience information?

First, we were looking to combine frequency- and experience cues in a way that's both cognitively plausible and computationally affordable. We considered three options (see

Fig. 3): (1) A combined expression that takes the average experience per observed option and multiplies it with the standard conformity terms:

$$P_{S,i,t+1} = \frac{n_{i,t}^{f} \exp(\beta \bar{E}_{i,t})}{\sum\limits_{i=1}^{4} n_{i,t}^{f} \exp(\beta \bar{E}_{i,t})}, \tag{8}$$

where $\bar{E}_{i,t}$ is just the average experience level of all models that chose option i; (2) a pseudo-counts approach, where the observed number of choices per option $n_{i,t}$ is weighted by the relative experiences of models choosing this option:

$$P_{S,i,t+1} = \frac{(\sum\limits_{j=1}^{n_{i,t}} \exp(\beta E_{j,t}))^{f}}{\sum\limits_{i=1}^{4} (\sum\limits_{j=1}^{n_{i,t}} \exp(\beta E_{j,t}))^{f}}, \tag{9}$$

and (3) the convex combination formulation described above. (2) was found to result in some implausible outcomes, such as higher conformity exponents leading individuals to favor the minority option when the model holding this option is attended to because of experience-directed learning (see center column in Fig. 3). Therefore, we only simulated data from options (1) and (3) and made sure our models would recover the correct direction and relative strength of both learning strategies. Option (3) will be used for the statistical analysis, because convex combinations are relatively easy to estimate, κ gives us a direct estimate of the relative strength of both kinds of cues and this form of parameterization allows conformity to operate on a choice basis and experience bias on an individual basis which is cognitively more plausible than (1) where experience bias is based on the average experience per option.

Table 2. Exemplary social information used for Fig. 3

	Model 1	Model 2	Model 3
Choice	1	1	4
Experience	5	10	4

Can we recover learning dynamics?

As described above, we explored different modelling strategies to make learning parameters σ (weight of social info), κ (relative influence of experience and frequency), f (conformity exponent) and β (strength and direction of experience bias) dynamic over time and specific to each individual. We fit individual-specific estimates for the other learning parameters as well but do not let them vary by experience, because those "background" learning variables are not our primary target of inference here. We aimed to find models that are flexible enough to detect abrupt changes in learning but are still possible to fit while avoiding the risk of overfitting. The model with separate intercepts (with or without pooling) for each level of experience for all social learning parameters and individuals did not fit reliably, most likely because this is just a crazy amount of parameters (9,600 for those

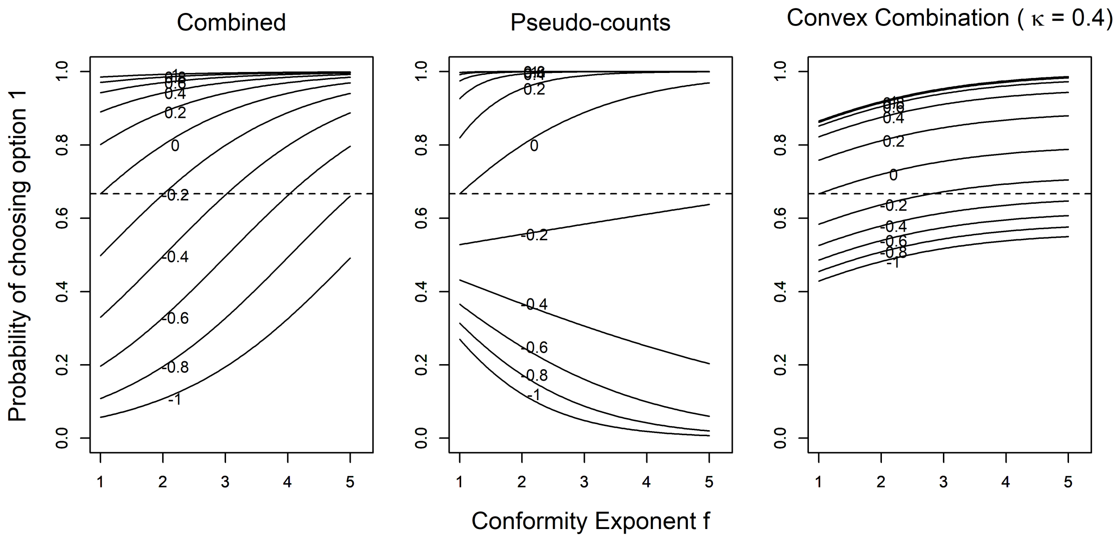

Figure 3. Probability that option 1 is chosen given the social information in Table 2 according to three different ways to combine frequency and experience information. Lines represent different values of experience bias parameter β. Unbiased, linear copying results in a probability of $\frac{2}{3}$ (indicated by the dashed line), because 2 of the 3 models chose option 1. Values of f above 1 indicate positive frequency dependence, if β is below 0 learners are biased towards less experienced individuals, if it is above 0 they are biased towards more experiences individuals.

parameters alone). Letting learning parameters change as a direct function of experience is much more parsimonious computationally. We used a logit link function for σ and κ (to keep parameters in interval [0,1]), a log link for f (to make it positive) and just an identity link (i.e. Gaussian) for β. This model could recover the average dynamics across all individuals reasonably well. However, there were some implausible individual-level estimates. Because of the exponential scaling of f for example, very small differences in the weight of experience among individuals led to massive differences on the outcome scale for high levels of experience. These functional expressions let us identify the general strength and direction of the effect of experience on learning, but are often too rigid to reproduce the exact trajectories.

Third, we ran a model where experience was used as an ordered categorical predictor for all 4 social learning parameters. We chose very weak Dirichlet priors for the respective δ_j simplexes so that sudden switches in learning strategies could be represented. The results of this model are shown in Figure 4. Using the monotonic effects approach, we could reliably uncover all changes in σ, f and β that we simulated here. For σ, we included two different "types" of learners on top of considerable inter-individual variation. Half of simulated agents rely heavily on social learning in the beginning and then switch completely to individual learning after a couple of rounds, while the rest relies on intermediate amounts of social learning irrespective of experience. Individuals start conforming to the majority and attending to the most experienced individuals. After 5 rounds, they switch to linear copying (i.e. no conformity) that is directed at the youngest individuals. This is exactly the result we get from the model. Although these results are very encouraging, the monotonic

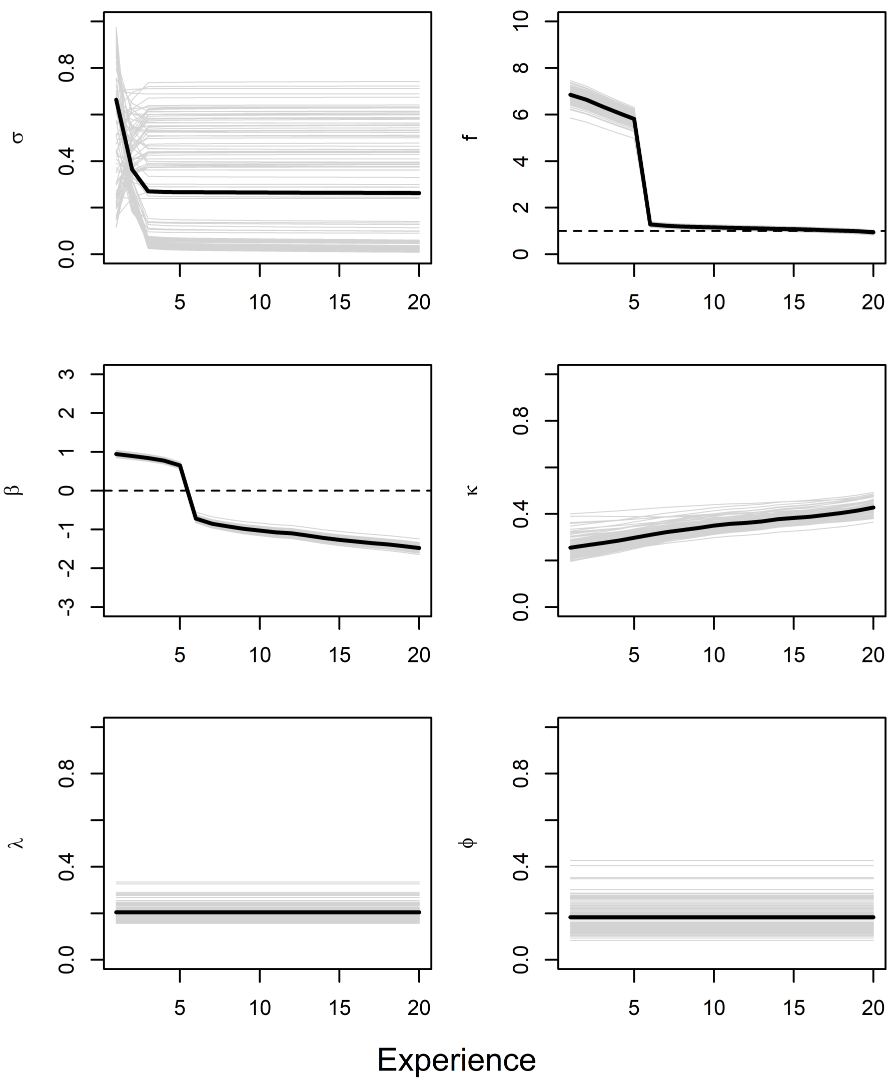

Figure 4. Monotonic effect regressions for different model parameters conditional on the level of experience. Grey lines represent individual-level estimates for 120 simulated participants, the solid black lines are the averages over all participants. For σ, we simulated two different "types" of learners. Half of simulated agents rely heavily on social learning in the beginning and then switch completely to individual learning after a couple of rounds, while the rest relies on intermediate amounts of social learning irrespective of experience.

effects approach still relies on the (albeit plausible) assumption that parameters change monotonically as individuals become more experienced.

In the most complex models that do not make any such assumptions, we include Gaussian process regressions for σ, κ, f and β. To include inter-individual variation, we let each η^2, ρ^2 and σ^2 vary by individual and estimate a unique variance-covariance matrix for each parameter and individual. Unfortunately, this model was too complex to fit reliably, indicated by many divergent transitions as well as other divergence diagnostics. Looking at the

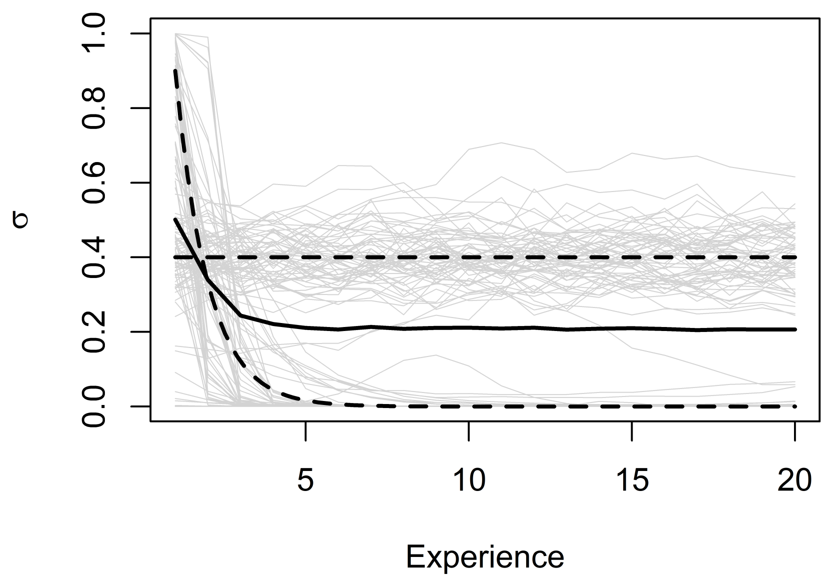

Figure 5. Gaussian process regression for the weight of social learning σ conditional on the level of experience. Grey lines represent individual-level estimates for 120 simulated participants, the solid black line is the average over all participants. Dashed lines represent two simulated learning types.

respective Gaussian process hyperparameters revealed that the model could only reliably estimate (hyper-)parameters for σ, but not for f, β or κ where the model essentially returned the priors we specified. In line with that, this model reliably recovered the simulated learning curves for σ (see Fig. 5) including the two different learning types we simulated (dashed lines), but not for the other learning parameters, for which the model returned rather flat curves.

Our aim here is not necessarily to nominate a single "optimal" model, as each modelling option has its own benefits and problems. Instead, we plan to run multiple models on the experimental data and make sure they lead us to the same general inferences. Where they do, we can be confident about the conclusions we draw, where they do not, we can still learn a lot from the differences between different models as we know how they behave on simulated data. A similar approach has been put forward by Steegen et al. (2016) who propose to run a "multiverse" analysis on all possible datasets that can justifiably be constructed from primary empirical data to get an idea about how much the conclusions change because of arbitrary choices in data construction. While "p-hacking" means trying out several analyses and reporting just the ones that worked, such multiverse analyses run and report multiple justifiable analyses and show whether the results hold under a variety of different modelling assumptions.

Predictions

- Compared to experiments with fixed groups, we predict a higher base rate of social learning, because overlapping "generations" allow accumulation of adaptive information in "older" age classes that newly arriving individuals can capitalize on.
-As there is no learning cost in this experiment, more learning opportunities should generally be associated with higher probabilities of choosing the optimal option. Therefore, overall individuals should tend to copy more experienced rather then less experienced individuals.
-Learning co-varies with experience in group: As individuals enter new groups, they should rely more heavily on social learning. In particular, they should attend to the most experienced individuals and tend to copy the majority option. As individuals become more experienced, they should rely more heavily on personal information and should be less prone to copy the majority and (other) highly-experienced individuals.
-Compared to learning after migration (spatial change in the environment), temporal changes in the environment should result in less reliance on social learning, as other individuals became non-adapted at the same time. Individuals should be less likely to copy the majority (see Nakahashi et al. (2012)) and experience cues should not be attended to, as there should be no correlation between experience in a region and adaptive knowledge after the environment has changed.

References

Baum, W. M., Richerson, P. J., Efferson, C. M., & Paciotti, B. M. (2004). Cultural evolution in laboratory microsocieties including traditions of rule giving and rule following. *Evolution and Human Behavior*, *25*(5), 305–326.

Boyd, R., & Richerson, P. J. (1988). *Culture and the evolutionary process.* University of Chicago press.

Camerer, C., & Hua Ho, T. (1999). Experience-weighted attraction learning in normal form games. *Econometrica*, *67*(4), 827–874.

Efferson, C., Lalive, R., Richerson, P. J., McElreath, R., & Lubell, M. (2008). Conformists and mavericks: the empirics of frequency-dependent cultural transmission. *Evolution and Human Behavior*, *29*(1), 56–64.

Hoppitt, W., & Laland, K. N. (2013). *Social learning: an introduction to mechanisms, methods, and models.* Princeton University Press.

Kendal, R. L., Boogert, N. J., Rendell, L., Laland, K. N., Webster, M., & Jones, P. L. (2018). Social learning strategies: Bridge-building between fields. *Trends in cognitive sciences*, *22*(7), 651–665.

Laland, K. N. (2004). Social learning strategies. *Animal Learning & Behavior*, *32*(1), 4–14.

McElreath, R., Bell, A. V., Efferson, C., Lubell, M., Richerson, P. J., & Waring, T. (2008). Beyond existence and aiming outside the laboratory: estimating frequency-dependent and pay-off-biased social learning strategies. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1509), 3515–3528.

McElreath, R., Lubell, M., Richerson, P. J., Waring, T. M., Baum, W., Edsten, E., ... Paciotti, B. (2005). Applying evolutionary models to the laboratory study of social learning. *Evolution and Human Behavior*, *26*(6), 483–508.

Mesoudi, A. (2018). Migration, acculturation, and the maintenance of between-group cultural variation. *PloS one*, *13*(10), e0205573.

Morgan, T., Rendell, L., Ehn, M., Hoppitt, W., & Laland, K. (2011). The evolutionary basis of human social learning. *Proceedings of the Royal Society B: Biological Sciences*, *279*(1729), 653–662.

Nakahashi, W., Wakano, J. Y., & Henrich, J. (2012). Adaptive social learning strategies in temporally and spatially varying environments. *Human Nature*, *23*(4), 386–418.

Schotter, A., & Sopher, B. (2003). Social learning and coordination conventions in intergenerational games: An experimental study. *Journal of political economy*, *111*(3), 498–529.

Steegen, S., Tuerlinckx, F., Gelman, A., & Vanpaemel, W. (2016). Increasing transparency through a multiverse analysis. *Perspectives on Psychological Science*, *11*(5), 702–712.

Toyokawa, W., Whalen, A., & Laland, K. N. (2019). Social learning strategies regulate the wisdom and madness of interactive crowds. *Nature Human Behaviour*, *3*(2), 183.