Research Proposal

Prestige as a Driving Force in Cultural Transmission

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Introduction

Cultural transmission is the way individuals inherit cultural traits from one another, typically via learning or copying. It is common in humans (Cavalli-Sforza and Feldman, 1981, pg. 3), and in primates, such as chimpanzees (Horner et al., 2010; Kendal et al., 2015). The common cultural traits in humans are behavioural patterns, like personalities and habits, transmitted via observations and verbal discussions (Henrich and McElreath, 2007). They suggest that cultural learning may be particular to humans, but McComb et al. (2001) suggest that it appears in other mammals, such as elephants. They demonstrated that:

> ... the possession of enhanced discriminatory abilities by the oldest individual in a group can influence the social knowledge of the group as a whole.

They showed that once a matriarch is removed from the group, the group's survival instincts are inferior. They did that by playing audio recordings of African elephants, and showed that groups with a matriarch recognise and react better to hostile or friendly calls than the groups without one. It appears that cultural transmission appears in other species, which are simpler than mammals, such as *Drosophila*. Battesti et al. (2012) show that oviposition site choice in fruit flies is culturally transmitted. They showed that flies without experience in choosing sites, after spending some time with experienced flies, chose the same type of site without directly observing this behaviour. Battesti et al. (2012) mention that the how the information is transferred is still an open question, but suggest that the flies may use olfactory cues, like other animals, such as rodents and bees.

It appears cultural transmission is similar to genetic transmission in many ways, while very different in others. Similar to genetic transmission, the effects of culturally transmitted traits can be physiological rather than behavioural, and transmitted from parents to offspring.For example, parents can teach their children to be strong or tall, within some biological limits, when they tell them to eat healthy and engage in physical exercises. Contrary to genetic transmission, the sources of the traits can be teachers, celebrities, coaches, the media, or any stranger that comes in contact with them. Cultural transmission can be vertical, where parents transmit to their children, but also oblique, where other adults transmit traits to children (not their own). Horizontal transmission is also possible, where peers transmit traits to one another. Lastly, vertical transmission in the opposite direction is possible too, where parents copy traits from their children (Cavalli-Sforza and Feldman, 1981; Creanza et al., 2017). In addition, even when a cultural trait is disfavoured by natural selection, it still may spread across a population given transmission biases (Boyd and Richerson, 1988, Ch. 8 pg. 279).

Transmission bias occurs when a trait has a disproportionate probability to be transmitted. For example, Eickbush et al. (2019) showed that there are genes of yeast (called *wtf genes*) that bias their transmission to the gametes. They secrete a long life expectancy poison, together with a short life expectancy antidote, so a gamete without the gene will perish (the poison will outlive the antidote). Transmission biases, though exist in genetic transmission, are probably more common in cultural transmission. Rendell et al. (2010) suggest that success biased social transmission contribute more to the general success of the population than individual learning. They conducted a tournament for developing learning strategies of a population, where each participant need to suggest a strategy. Each strategy must define when individuals should observe and copy from others, and when to engage in individual learning. The best strategies contained a high percentage of social learning, even when the error when copying was as high as almost 0.5. In addition to Rendell et al. (2010), Fogarty et al. (2017) define different types of transmission biases based on success. They define several types of role model choosing methods, all assuming that the copier correctly identifies the successful ones. Both studies assume that individuals can successfully evaluate successful individuals. Boyd and Richerson (1988, Ch. 5) suggest that the evaluation of success can be divided into three groups - *direct bias*, *indirect bias* and *frequency-dependant bias*. A direct bias is when a variation of a trait is more attractive than others, and is evaluated by *directly* testing the variation of the trait. For example, an individual observing a Ping-Pong match between two others can try both paddle grips it observed, and decide what grip is better for it. An indirect bias is when an individual uses the value of one trait to determine the attractiveness of another, so it *indirectly* evaluates the attractiveness of the trait. Following the example, a bystander could copy the paddle grip of the more successful Ping-Pong player (by keeping score for example). A frequency-dependant bias is when an offspring has a probability to copy a variant of the trait that is nonlinear to the trait's frequency in the parent's generation. Continuing with the example, an individual copying the grip most players use, is affected by the *frequency* this of this grip in the population.

Prestige refers to a good reputation or high-esteem, therefore does not directly signify success (although it may imply it), making it an *indirect bias*. Both Boyd and Richerson (1988, Ch. 8) and Fogarty et al. (2017) claim that prestige biases are probably more common in humans than success biases. Boyd and Richerson (1988, Ch. 8) add that maladaptive traits may spread widely in a population, if the indirect bias is strong enough. They claim the bias could lead to a *runaway process*, caused by a cultural equivalent of *sexual selection* (Andersson, 1994). On the other hand, Henrich and Broesch (2011) claim that prestige biases, over generations, can lead to cultural adaptations. Hence prestige can cause a maladaptive trait to spread in the population, but can also accelerate the spread of adaptive traits. Prestige bias is mentioned in the literature many times, but rarely modelled. Boyd and Richerson (1988) have modelled the prestige bias, but didn't include the effects the copiers of a role model has on the probability of other individuals to choose the same role model.

This effect is similar to conformity, which is usually modelled as a different bias. Boyd and Richerson (1988) have suggested a model for *frequency dependant biases*, which include conformity bias. *Conformist learning* (imitating locally common behaviours) is a known bias in cultural transmission (Molleman et al., 2013). Our new component, *influence*, is assigned to a role model, contrary to conformity, which refers to the probability of a specific variation of a trait. If we define the copying of a role model i as a trait itself, then *influence* falls under the category of conformity. We believe that prestige bias is a combination of the *indirect bias* as Boyd and Richerson (1988) suggest, and of the *influence* a role model has on the population. **The goal of this study is to define a more realistic model for prestige bias and analyse the dynamics of the population it causes**. Today, due to social media, it is easier than ever to estimate the influence individuals have over others, therefore it is probably a major part of our decision-making process. We want to create a model that better fits reality, and simulate scenarios that better mimic cultural transmission dynamics. With a more accurate model of prestige bias, we can understand better how cultural traits are transmitted, and why. Moreover, we could explain better the cause for the spread of maladaptive traits, or the acceleration of adaptive traits in reality.

Research plan

General model. Consider a large population with N individuals, with non-overlapping generations. Every individual has two types of traits - *role model traits*, and *copier traits*. **Role model traits** are composed of: an *indicator trait*, which affects the attractiveness of the role model; *indirectly biased trait*, which may affect the fitness of the role model, but doesn't affect its attractiveness; and *influence*, which is the number of other copiers that chose this role model, weighted by their own *influence*, and also affects the role model's attractiveness. For example, an amateur hunter who wants to choose a role model to copy, cannot follow all the hunters in its village, because it is impractical. The amateur needs another indication that signals success, for example: the quality or the size of the spear that a role model carries. However, the amateur understands that the spear isn't the sole source of the hunter's success, only implies it, and therefore he copies other behaviours too: face paint, schedule, and other rituals the chosen role model performs. The spear's features (quality or size) are therefore *indicator traits*, while the other rituals copied are *indirectly biased traits* (indirect traits in short). We also assume a hunter copied by other prestigious hunters, is more valued than a hunter copied by the same number of amateur hunters. Each copier (naive individual) evaluates the prestige of each available role model by estimating its indicator trait and influence values and chooses one based on it. Transmission is based on cultural biases only. Natural selection is not taken into consideration in this model. The prestige score of role model i out of N is:

$$P_i = A_i + R_i, \tag{1}$$

where A_i is the indicator trait value of role model i, $A_i \in \mathbb{R}$, and R_i is the influence value of the role model, given by:

$$R_i = 1 + \sum_{j=1}^{k} R_j, \tag{2}$$

where k is the number of current copiers of role model i, and $R_i \geq 1$ (the influence of a role model with no copiers is 1, to avoid nullification of the recursive equation). The equation is always satisfied because there cannot be any cycles in the copying order: assume individual j copied from individual i, by the model's design, it means individual i didn't copy individual j, nor any descendant of it, because j doesn't have any copiers of its own at the moment of copying from i. Equation (2) describes a solution for a weighted ranking problem, resembling the PageRank algorithm (Xing and Ghorbani, 2004).

Equation (1) implies that every copier j evaluates role model's i prestige equally. We assume each copier values the indicator trait and the influence trait differently - some hunters may be more impressed by spear size, regardless of number of copiers. Therefore, naive individuals are born with **copier traits**, to differentiate their estimation process from one another: *indicator weight* and *influence weight* are traits that control the importance of the indicator and influence traits for copier j. P_{ij} is the prestige score of role model i, evaluated by copier j such that:

$$P_{ij} = \alpha_j A_i + (1 - \alpha_j) R_i, \tag{3}$$

where α_j and $1-\alpha_j$ are the weights of the indicator and influence traits ,respectively, and $\alpha_j \in [0, 1]$. Equation (3) implies that the higher the indicator and influence values are, the more prestigious the role model. However, a higher indicator doesn't always mean higher prestige: a spear the size of the moon is impractical, therefore we define an ideal value for the indicator trait. Here, we keep the assumption that high influence is always better, though in reality that isn't always the case. The optimal indicator value is another copier trait, and could be homogenous or individually assigned. We call it the *preference trait*, $\hat{A}_j$:

$$P_{ij} = \alpha_j \beta(A_i, \hat{A}_j) + (1 - \alpha_j) R_i \tag{4}$$

where β is the *bias function*, such that: $\beta(A, \hat{A}) = b * e^{\frac{-(A-\hat{A})^2}{2J}}$, and J, b are parameters to control the strength of the bias. In our models the preference trait is homogenous: i.e all the copiers have the same preference trait value, so without loss of generality, we define $\hat{A}_j = 1$ for every j. The closer the indicator value of the role model to the copier's preference trait, the greater the bias.
Equation (4) implies that every copier evaluates the traits equally and accurately. In real life, not all copiers have the same access to the role models' spears. Moreover, even given access to measure the spears' sizes, it would be very time consuming, so amateur copiers need to evaluate the spears by observing them. Therefore, we assume each copier is capable of different levels of accuracy, so each copier is born with its own error values for estimating indicator values e_A (we assume influence can be measured easily, therefore it is accurate):

$$P_{ij} = \alpha_j \beta((A_i + e_{jA}), \hat{A}) + (1 - \alpha_j) R_i \tag{5}$$

This model is inspired by the model Boyd and Richerson (Ch. 8 1988, pg. 243-244) suggest for an indirect bias.

After evaluating the prestige scores of all available role models, the copier chooses a role model to copy with a probability $Pr(j|i)$ such that:

$$P_r(j|i) = \frac{P_{ij}}{\sum\limits_{i=1}^{N} P_{ij}} \tag{6}$$

Once a role model is chosen, the indicator and indirect traits A_i, B_i are transmitted with errors:

$$(A_j, B_j) = (A_i + e_{jA}, B_i + e_{jB}), \tag{7}$$

where j is the index of the copier that chose role model i as its role model, $B \in \mathbb{R}$, and e_B is the indirect trait error. We assume influence cannot be transmitted, only acquired by being copied by others. In the first generation, the indicator and indirect traits are drawn from a 2D normal distribution, with a correlation of χ. The errors are drawn from a 2D normal distribution as well, for each naive copier born, with ζ correlation, and scaled down by the *error scale* parameter η.

Once all the copiers are informed they replace the role models' generation, and a new naive generation of copiers is born.

Aim 1: strengthening our alternative transmission mode: the random choice transmission. To support our suggested model, we first compare it with Boyd and Richerson (1988) indirect bias model to show that it achieves similar results. The most significant difference between our model and theirs, is the additional influence trait, and the transmission mode. In their model, Boyd and Richerson (1988) suggest a transmission mode called *blending transmission*. The concept of the blending mode is the following: each naive individual copies an average of all the role models' traits, weighted by their prestige score, instead of choosing one at random. In their model, Boyd and Richerson (1988) use two different bias functions: one for each trait, and both take only the preference trait and the indicator trait as parameters. This results in two prestige scores for each role model, distinguished by a slight magnitude difference. Each of the traits is then transmitted separately, depending only on its respective score. In addition, the prestige score is modified by a basic social rank, that is drawn randomly at birth. To maintain minimum difference, we assume indicator weight $\alpha_j = 0$ for every copier j, to eliminate the influence value in this model.

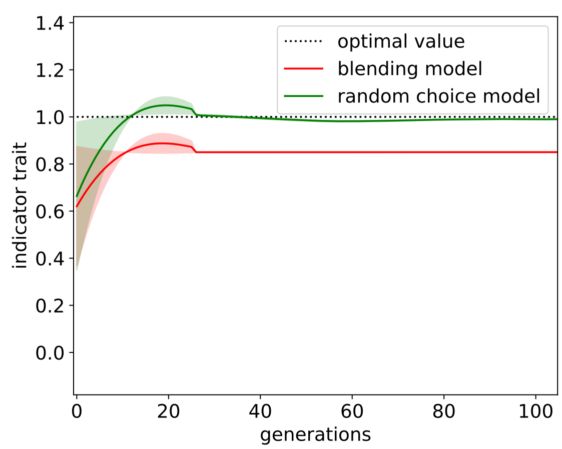
Including the basic social rank, in this comparison model, the prestige evaluation equation is

$$P_{ij} = \tau_i + \beta((A_i + e_{jA}), \hat{A}), \tag{8}$$

where τ_i is the social rank of role model i, drawn at random from the interval $[0, \beta((A_i + e_{jA}), \hat{A})]$, to avoid overshadowing the indicator trait value significance. We assume generations are non-overlapping, and transmission is oblique only. The expected value of a trait X (either indicator or indirect) when copier i is choosing a model is: $E[X] = \sum_{j=1}^{n} A_j P_{ij}$, which is the equation for the blending mode transmission (Boyd and Richerson, 1988, eq. 8.9, 8.10). The population in both models is finite, but is supposedly large enough so that $Var(X)$ is small.

Preliminary results. We compare our suggested transmission mode, the random choice mode (eq.6), with the blending transmission mode Boyd and Richerson (1988, eq. 8.9, 8.10) have suggested. We tested several cases, the most interesting being those with a high correlation value between indicator and indirect trait values. Figure 1 shows a single simulation with high initial traits correlation $\chi = 0.9$, relatively small population size, $N = 1000$, over 1000 generations. Starting population is the same in both simulations of transmission modes (blending and random choice).

(a) Indicator trait evolution



(b) Indirectly biased trait evolution

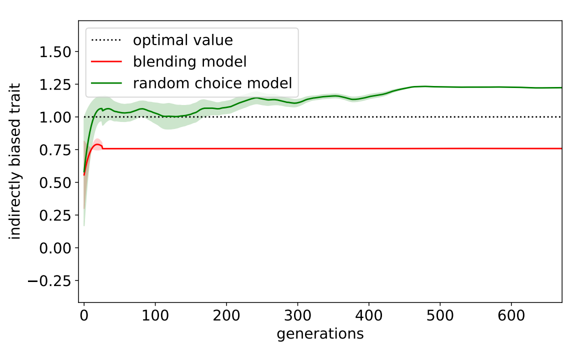


Figure 1: Blending vs Random Choice model. Faded is standard deviation. Population size 1000. Single simulation, initial trait values chosen from a 2D normal distribution with a 0.9 correlation. Starting population the same in both realisations. Faded area represents standard deviation

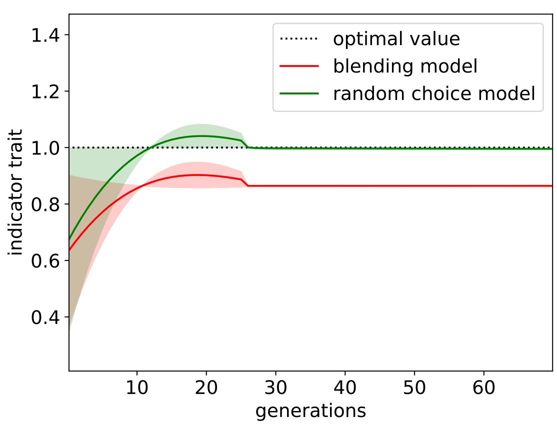
We see that both transmission modes result in a mean indicator value that is converging towards the optimal value in the beginning. However, when using the blending transmission mode the population becomes homogenous in a very early stage, therefore probably preventing the mean value to converge to the optimum. In both transmission modes the mean indirect trait value doesn't converge to the optimal indicator value, even though the initial correlation between the traits was very high. When using the blending transmission the variance is again converging to zero very fast, but in the random choice transmission the mean value becomes stable much later.

When calculating the mean values of 20 simulations, with the same parameters, the results are a bit different, as seen in Figure 2.
We see that when using either of the transmission modes, the mean indicator values both converge to the optimal value (random choice converging to a closer value), and the variance is converging to zero in a very early stage. The difference between the two transmission modes when observing the indirect value is

more prominent. When using the blending mode the variance is still converging to zero very fast, and the stable value of the indirect trait doesn't reach the optimal indicator value, nor the mean indicator value. When using the random choice model, we see that the variance is relatively large at the beginning, and slowly converging to zero towards the end of the simulation. We also see that the mean indirect value converges to the optimal indicator value, meaning that the initial correlation sufficed when using this transmission mode. We believe that the variance of the blending mode will not converge to zero as quickly only if the error scale we use is considerably larger. By the definition of the blending mode (a weighted average), we believe that even when injecting a single optimal role model each generation, the mean indicator value will not reach the optimal value as fast as in the random choice mode.

Aim 2: creating a basic yet realistic model that includes influence, and analyse the dynamics in the population. We believe that influence may have significant effects on the mean value of the indicator and indirect traits in the population, even in its most basic form. Therefore we define a simple version of our model where we limit the transmission to oblique transmission only (and the generations are still discrete). This model has several variations: **homogenous weights**, where every individual has the same weights α; **random weights**, where every individual has (different) random weights α_j; **transmitted correlated weights**, where the weights are correlated to the traits of the first role models' generation, and the copier copies the weights of the role model (accurately) $\alpha_j = \alpha_i$. The transmission mode we use is the random choice transmission, so we can keep track who copied from whom. Since generations are discrete, influence is "shallow", meaning it is equal to the number of copiers. For every role model evaluated by each of the copiers, we count the number of copiers who chose this role model, and calculate the score accordingly. The evaluation process

(a) Indicator trait evolution



(b) Indirectly biased trait evolution

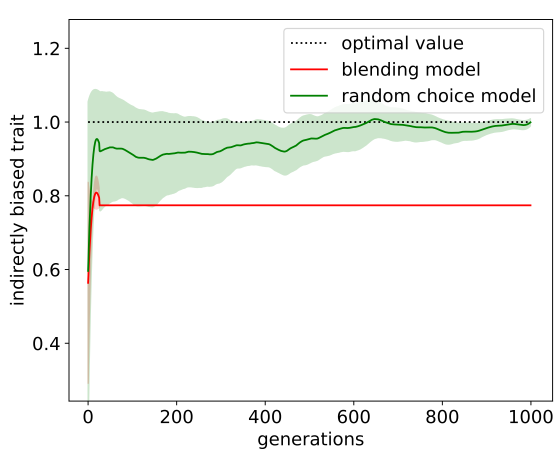


Figure 2: Blending vs Random Choice model. Population size 1000. Mean values of 20 simulations, initial trait values chosen from a 2D normal distribution with a 0.9 correlation (chosen randomly in each simulation). Faded area represents mean of standard deviation

is according to equation (5). We expect that the homogenous weights variation will increase the variance both indicator and indirect traits, compared to the atrophied version of our model described in step 1. We believe that the higher the influence weight will be, the higher the variance of both traits will be. We also expect that the when the variance of the traits will converge to zero, the maximum influence value will decrease as well, because the role models will have similar indicator values, therefore similar prestige scores. We believe that the variation in reality isn't homogenous, therefore we want to compare the opposite (random weights) to see if the results are more reasonable. We assume that the mean and variance of both traits in the random weights variation will be similar to homogenous equal weights, $\alpha = 0.5$. The last variation, the transmitted correlated weights, is probably the most realistic scenario: when an individual is valued for his remarkable indicator value, he will probably value it more in others. We expect that when the correlation is high, the mean influence weight will converge to 0, or decrease significantly between generations.

Preliminary results. We ran 35 simulations, population size $N = 5000$, indicator-indirect traits correlation $\chi = 0.9$, with different starting generation each simulation, and error scale $\eta = 100$. The model variation we tested is the random weights variation, and the results are shown in Figure 3. We see several differences between this model and the variation without any influence: The variance of both indicator and indirect traits is larger than before, and don't converge to zero; The indirect trait mean doesn't converge to the optimal indicator value, and even drifts away in the later generations; The indirect trait mean is stabler than the previous model using the random choice transmission mode; The indicator mean value takes longer to converge to the optimal value (the 200th generation vs. the 30th). These results could be caused by both the larger population size N, and smaller error scale η alone, but can also be caused by the addition of the influence to the bias score. Our next step would be to test more variations of the model's parameters in the earlier variation mentioned in **Aim 1**, and determine the real cause of difference between results.

Aim 3: increasing our model's realisticness by adding horizontal transmission. We believe that in reality, individuals often copy from their own peers, so we create a model that allows a basic form horizontal transmission. We think that with horizontal transmission our model is more realistic than a simple non-overlapping model. Therefore, we allow horizontal transmission, in addition to oblique

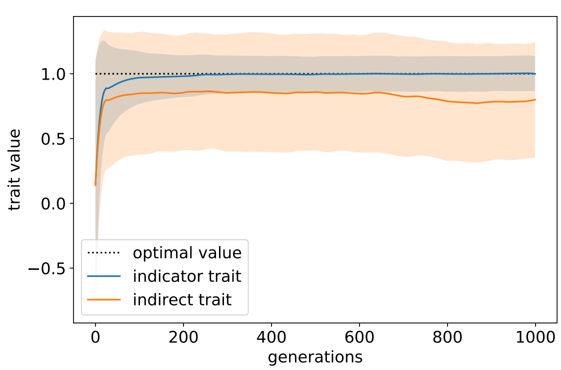


Figure 3: Basic influence model. Population size 5000. Mean values of 35 simulations, initial trait values chosen from a 2D normal distribution with

transmission, to see how it affects the convergence pace of the traits to a stable value. Here, every copier becomes an available role model instantly after being informed, so its peers could copy from it as well. The influence is now a recursive equation, contrary to the simple counter it was in the previous step. Once all the copiers are informed, the older generation disappears, and the process is repeated. We expect that the maximum influence value in every generation will be higher than the model with oblique transmission only. We also expect that the high influence will slow down the convergence of the traits to the optimum value, and perhaps increase the variance even more.

Aim 4: creating a more realistic model by including natural selection and overlapping generations. In some populations, the transmission model of non-overlapping generations may not be realistic enough. We therefore define a model that allows an individual to be copied by many generations, same as a village elder that may pass on its knowledge up to 3 generations after his own. Consider a population of N individuals, all born with random indicator and indirect trait values as before. Every cycle (time unit), one naive individual is born and chooses a role model, he becomes an available role model itself. In order to bring our model closer to reality, we will add dynamics of *natural selection* by biasing the chance of death with the value of the indirectly biased trait. Every d cycles (d could be one cycle), k role models "die", depending on several parameters (we assume $k << N$): **number of cycles alive**: the longer it lived, the greater the chance it would die, i.e dies of old age; **random misfortune**: a random value drawn at the moment of evaluation, i.e chance to die in an accident; **natural selection**: the indirect trait is either favoured or disfavoured by natural selection. The death score D_i of role model i is given by:

$$D_i = r + a_i + s * B_i, \tag{9}$$

where r is *random misfortune*: a random normal variable drawn at the moment of evaluation. a_i is the "age" (i.e number of cycles alive), and s is the strength of natural selection where B_i is the indirect trait value. The probability of role model i to die is given by:

$$P_d(i) = \frac{D_i}{\sum_{j=1}^{m} D_j}, \tag{10}$$

where m is the number of current available role models. We expect that the higher d (number of cycles before death), and the lower the k, the maximum influence per cycle will increase. We also expect that when the correlation between the indicator and indirect traits is high ($\chi > 0.7$), and natural selection disfavours the optimal indicator trait value ($\hat{A}$). Then the indirect and indicator traits will both still converge to the optimal value, given natural selection is weak enough, therefore decreasing the mean fitness of the population, i.e a *runaway process*.

Conclusion

Cultural transmission is the phenomenon of which cultural elements, in the form of attitudes, values, beliefs, and behavioural patterns, are transmitted. Some cultural traits can be more likely to be copied by others, regardless of their frequency in the population. Such transmission biases are common in cultural transmission processes. Many models are based on the assumption that success can be correctly identified, and easily copied. Here we assume that success isn't correctly identified, therefore individuals may use other indicators to try and estimate the success of others. We believe, as Fogarty et al. (2017) suggest, that *prestige biases* are more common in nature than success biases, since estimating success is probably harder. We believe prestige is composed of two main components: a trait that indicates success (but doesn't guarantee it), and the influence the individual already has on others. We created a model for *prestige bias*, following the *indirect bias* model Boyd and Richerson (1988) have suggested, and added the *influence trait* to it. We believe that in this era of social media and "likes" and "tagging" it is even easier than 20 years ago to estimate one's influence over others. Hence it is crucial to model the cultural biases more realisticly, and we believe including influence in the definition of prestige bias will help achieve that. With a more realistic model of a very common cultural transmission bias, we may be able to better understand decision-making processes in humans, including life-changing choices such as occupation or a life partner. Our model can be expanded in many ways: observing the effects of different bias functions, including errors in estimating the influence, combining factors of cost when copying from an influential role model (not all could afford to copy from the most popular role model), and analysing the differences when including several optimal values for the indicator trait (multiple preference traits in the population).

Appendix A - Time table

Today - Feb. 2020: We will improve the performance of the simulations, allowing us to test scenarios of larger populations the size of 10,000 or more. We might reach different conclusions regarding the blending mode transmission, given a considerably larger population.

Feb - Apr 2020: Achieving Aim 2, allowing us to test the effects of *influence* on the population.

Apr - Jun 2020: Achieving Aim 3, allowing us to observe the difference horizontal transmission can cause on the variance and mean value of the traits in the population.

Jun - Sep 2020: Achieving Aim 4, allowing us to observe an increasing force of *influence* on the population, and better understand the effects of it on the mean fitness of the population.

Sep - Nov 2020: Combining the results of the various models into a paper, and submitting for publication.

References

Andersson, M. B. (1994). *Sexual selection.* Princeton University Press.

Battesti, M., Moreno, C., Joly, D., and Mery, F. (2012). Spread of social information and dynamics of social transmission within drosophila groups. *Current Biology*, 22(4):309 – 313.

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

Cavalli-Sforza, L. L. and Feldman, M. W. (1981). *Cultural transmission and evolution: A quantitative approach.* Number 16. Princeton University Press.

Creanza, N., Kolodny, O., and Feldman, M. W. (2017). Cultural evolutionary theory: How culture evolves and why it matters. *Proceedings of the National Academy of Sciences*, 114(30):7782–7789.

Eickbush, M. T., Young, J. M., and Zanders, S. E. (2019). Killer meiotic drive and dynamic evolution of the wtf gene family. *Molecular biology and evolution*, 36(6):1201–1214.

Fogarty, L., Wakano, J. Y., Feldman, M. W., and Aoki, K. (2017). The driving forces of cultural complexity. *Human Nature*, 28(1):39–52.

Henrich, J. and Broesch, J. (2011). On the nature of cultural transmission networks: evidence from fijian villages for adaptive learning biases. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 366(1567):1139–1148.

Henrich, J. and McElreath, R. (2007). Dual-inheritance theory: the evolution of human cultural capacities and cultural evolution. In *Oxford handbook of evolutionary psychology.*

Horner, V., Proctor, D., Bonnie, K. E., Whiten, A., and de Waal, F. B. (2010). Prestige affects cultural learning in chimpanzees. *PloS one*, 5(5):e10625.

Kendal, R., Hopper, L. M., Whiten, A., Brosnan, S. F., Lambeth, S. P., Schapiro, S. J., and Hoppitt, W. (2015). Chimpanzees copy dominant and knowledgeable individuals: implications for cultural diversity. *Evolution and Human Behavior*, 36(1):65–72.

McComb, K., Moss, C., Durant, S. M., Baker, L., and Sayialel, S. (2001). Matriarchs as repositories of social knowledge in african elephants. *Science*, 292(5516):491–494.

Molleman, L., Pen, I., and Weissing, F. J. (2013). Effects of conformism on the cultural evolution of social behaviour. *PloS one*, 8(7):e68153.

Rendell, L., Boyd, R., Cownden, D., Enquist, M., Eriksson, K., Feldman, M. W., Fogarty, L., Ghirlanda, S., Lillicrap, T., and Laland, K. N. (2010). Why copy others? insights from the social learning strategies tournament. *Science*, 328(5975):208–213.

Xing, W. and Ghorbani, A. (2004). Weighted pagerank algorithm. In *Proceedings. Second Annual Conference on Communication Networks and Services Research, 2004.*, pages 305–314. IEEE.