Adaptive Observational Aversive Learning

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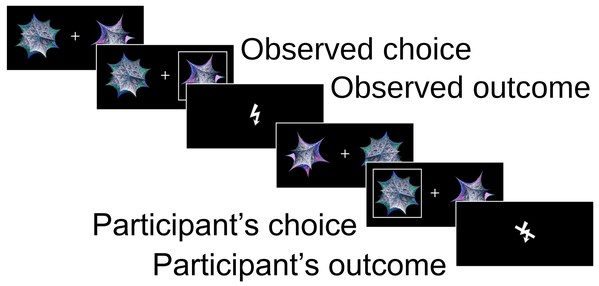
Introduction

- Observational learning, including associative learning (AL) and imitation from an observed model's outcome, complements individual learning.
- Imitation, but not associative learning, should be sensitive to the observed model's skill [1].
- We used an aversive learning task to examine how observational learning (imitation and AL) was affected by (i) the skill of the model and (ii) the amount of information available about the model's choice.

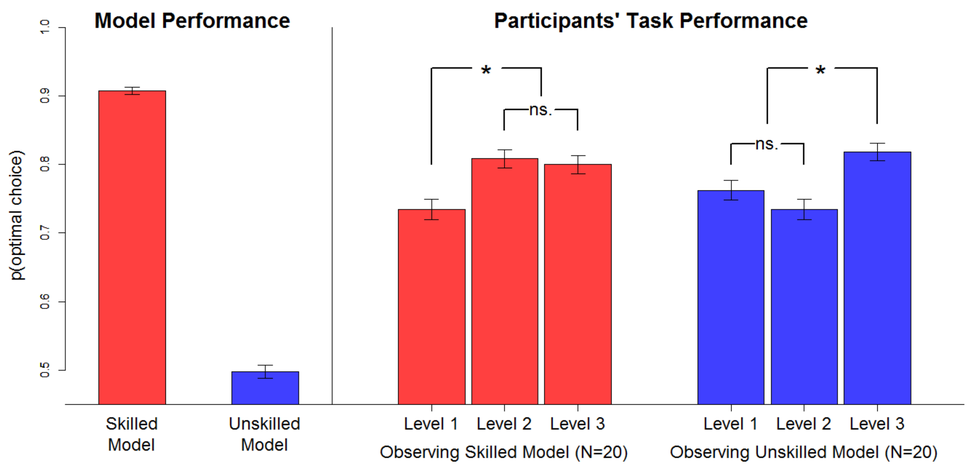


Method

- Probabilistic two-choice task with electric shocks as primary aversive reinforcers.
- Each trial consist of an observational phase followed by the participants own choice.

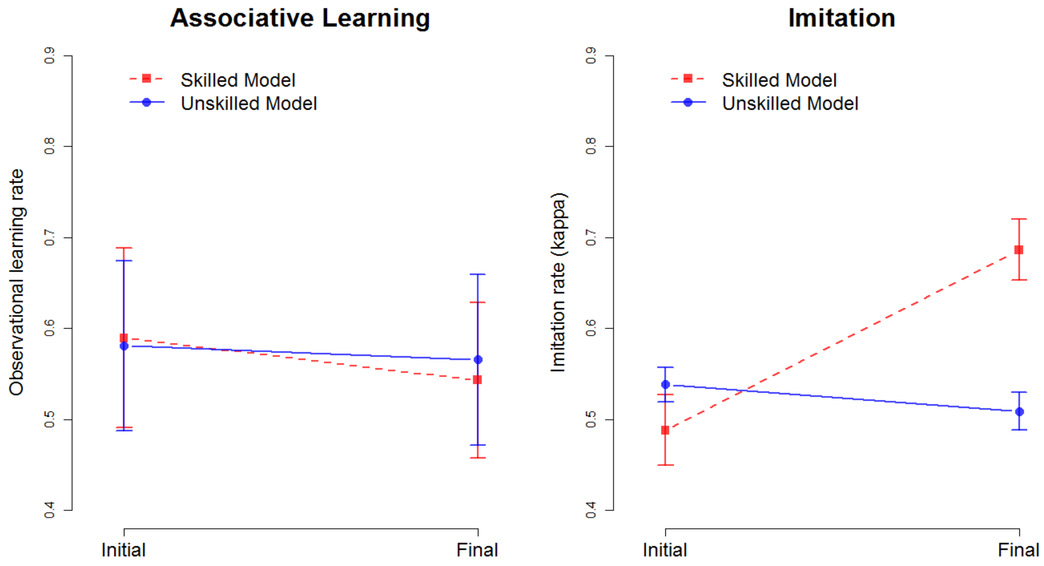
		Level of model observation		
	2x3 design	Level 1 No obser-vation	Level 2 Obs. of choice	Level 3 Obs. choice & outcome
Model Performance	Skilled (learns fast)	Skilled Level 1	Skilled Level 2	Skilled Level 3
	Unskilled (random)	Unskilled Level 1	Unskilled Level 2	Unskilled Level 3

Results



The interaction effect of Model Performance*Observation Level was driven by a difference in performance at Level 2, observation of model choice only.

RL analysis



The impact of model performance over time on observational associative learning and imitaion respectively was analyzed by fitting the learning parameters α_o and κ for each participant at an initial and final blcok of trials.

Conclusions

- Observational aversive learning of a skilled model leads to improved performance compared to individual learning, supportive of previous studies using secondary reinforcers [2].
- Observational learning from an unskilled model leads to improved performance compared to individual learning only when the model's outcome is observed.
- Participants adapt imitation to the observed model's skill and thus do not imitate suboptimal behavior.
- RL-modeling shows that adaption of learning was driven by an increase of imitation while observing a skilled model rather than a decrease while observing an unskilled model.

Reinforcement Learning (RL)

We used a modified Q-learning algorithm [2] to formalize observational RL.

Associative learning

- Q-values are updated after individual and observed outcomes using two learning rates, α_i (individual) and α_o (observed).

$$Q_c(t+1) = Q_c(t) + \alpha_{i,o} * (outcome_{i,o} - Q_c(t))$$

- The probability of choice is calculated using the softmax activation function:

$$p_c(t) = Softmax(Q_c, t) = \frac{\exp(Q_c(t)/\beta)}{\exp(Q_1(t)/\beta)+\exp(Q_2(t)/\beta)}$$

Imitation

- During observation of choice only (Level 2) the probability of choice was affected by imitation of the observed choice using an imitation rate, κ:

$$p_{obs.c}(t) = \kappa * \left(1 - p_{obs.c}(t-1)\right) + Softmax(Q_{obs.c}, t)$$

References:

[1] Enquist, M., Eriksson, K., Ghirlanda, S. (2007) Critical Social Learning: A Solution to Rogers's Paradox of Nonadaptive Culture, 109(4), 727-734

[2] Burke C., Tobler, P., Baddeley, M., Schultz, W. (2010) Neural Mechanisms of Observational Learning, *PNAS*, 107(32), 14431-14436

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