Model-Based Assimilation Transmits and Recombines World Models

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Abstract

We argue that imitation, in addition to the typical roles it plays in culture, additionally supports the social transmission and recombination of world models. We propose a learning pathway called "model-based assimilation", which uses imitation to shape the statics of experience, and "hijacks" existing individual learning mechanisms supporting model-based learning (e.g., hippocampal replay). This pathway is computationally cheaper than explicit Theory of Mind inference, but nevertheless allows for the social recombination of knowledge across multiple brains. Our theory provides important insights into why our close relative, the chimpanzee, imitates poorly and why humans acquired cumulative culture.

Keywords: Cultural evolution; Human evolution; Imitation; Reinforcement learning; Social learning

Introduction

Humans are a cultural species. We build up knowledge, skills, and institutions over multiple generations in a process known as cumulative cultural evolution (CCE). Social learning has long been identified as the key ability enabling cumulative culture, but the focus has largely been on the social transmission of observable actions. Why is it that cumulative culture is characteristic of human societies but not of other primates (Tennie, Bandini, van Schaik, & Hopper, 2020; Dean, Kendal, Schapiro, Thierry, & Laland, 2012)?

Here we describe a theory of how imitation supports the social recombination of knowledge across multiple brains. While humans are able to use Theory of Mind (ToM) to explicitly infer other people's world models, it can be costly due to computational intractability. Here we argue that humans — but not chimpanzees — are able to learn world models from others through a social learning pathway we call *model-based assimilation*. This pathway uses imitation to change the statistics of experience, and "hijacks" existing mechanisms (i.e., hippocampal replay) involved in asocial model-based learning. This mechanism combines social and individual world models, allowing for more creative and compositional innovations. In this way, humans get more from imitation than chimpanzees. This may explain why chimpanzees employ other types of social learning, but are unable to imitate new actions (Clay & Tennie, 2018; Neadle, Chappell, Clay, & Tennie, 2021). Model-based assimilation may thus be a key factor in the emergence of cumulative culture in humans, and we propose it as a target for future empirical research.

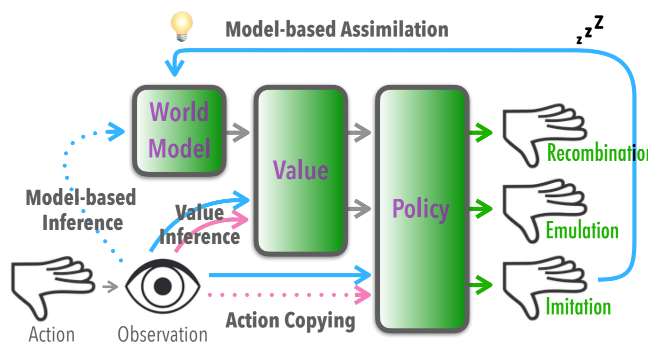

Figure 1: Social learning can operate over different pathways, each supported by different modalities of representation (green blocks). Colored arrows represent humans and chimpanzees, illustrating abilities that are pervasive (solid) or limited (dotted; e.g., due to computational cost) within-species. The *model-based assimilation* pathway uses imitation and hippocampal replay (zzz) to generate new causal insight (light bulb). See text for details.

Social Learning Hierarchy

The representational exchange framework of social learning (Wu, Vélez, & Cushman, 2022) describes how different social learning mechanisms form a hierarchy, trading off computational costs against flexibility and compositionality (Fig. 1). Socially observed behaviors can transmit (1) overt knowledge of the behavior itself ("action copying" to perform imitation), but can also be "unpacked" to (2) infer instrumental value and goal states ("value inference"), or (3) infer representations of the world, comprising the observed agents' beliefs and intrinsic reward function ("model-based inference"). We first introduce this hierarchy and then argue that its cost-benefit trade-offs help explain divergences between humans and chimpanzees.

Action copying involves directly copying socially observed behaviors:

$$P(A_{\text{self}}) \propto P(A_{\text{other}}). \tag{1}$$

In a reinforcement learning (RL) framework where actions are well-defined, copying actions is relatively cheap compared to other learning mechanisms requiring inference of hidden mental states. However, solving the “correspondence problem” may still add considerable costs (Nehaniv, Dautenhahn, et al., 2002), particularly for novel behaviors. Nevertheless, copied actions tend to lack flexibility in generalizing to differences in skills, preferences, or goals (Witt, Toyokawa, Lala, Gaissmaier, & Wu, in press).

Value inference involves “unpacking” observed actions into instrumental value representations (e.g., she goes to the supermarket across town, so it must have higher value). We can formulate value inference using Inverse Reinforcement Learning (IRL; Jara-Ettinger, Gweon, Schulz, & Tenenbaum, 2016), where we infer value V from observed actions A:

$$P(V|A) \propto P(A|V)P(V) \tag{2}$$

Whereas action copying operates over motor programs, value inference estimates representations of instrumental value (i.e., goals), requiring an extra layer of inference and incurring putatively greater computational costs (Wu et al., 2022). However, it may offer better generalization to new situations.

Model-based inference incurs higher computational costs than either value inference or action copying. This is because it requires, beyond value representations, further decomposition of observed behavior into the demonstrator’s presumed beliefs B about the causal structure of the world (i.e., state-state transition model), and their intrinsic reward function R:

$$P(B,R|A) \propto P(A|B,R)P(B,R) \tag{3}$$

A world model consisting of beliefs and desires can be used for the offline planning of actions. Moreover, a socially learned world model can be flexibly combined with one’s own model-based representations to realize known goals using new methods, or to discover new goals. Understanding causal primitives enables even better generalization than learning value representations, as they can be flexibly combined to generate new composite hypotheses about the environment, and adapted to new goals (Schwartenbeck et al., 2021). Informed by the cost-benefit trade-offs of this social learning hierarchy, we investigate an alternative pathway for model-based flexibility, but without paying the full costs of explicit ToM inference

Proposed Theory

We provide a neurocognitive explanation of how imitation supports model-based learning and the social recombination of world models. We use this theory to evaluate known cognitive differences between chimpanzees, and to help explain the human capacity for cumulative cultural evolution.

Hypothesis 1: Model-based assimilation. We propose that action copying changes the statistics of experience by selectively amplifying the frequency of some socially observed actions. Exposure to imitated actions unlocks a new learning pathway we call *model-based assimilation* (Fig. 1), which “hijacks” existing individual model-based learning mechanisms such as hippocampal replay (Kurth-Nelson et al., 2023; Eldar, Lièvre, Dayan, & Dolan, 2020) to incorporate social information into one’s world model. This allows humans to approximate MBI-like behavior, but bypassing the computational costs of explicitly performing ToM.

While humans are certainly capable of explicitly inferring hidden mental models of other people’s beliefs, it may not always be cost-effective to do so (Lieder & Griffiths, 2020). However, reusing existing neural mechanisms to solve new problems is an organizing principle of the brain (Anderson, 2010; Dehaene & Cohen, 2007). Thus, leveraging imitation and hippocampal replay to construct a socially informed world model provides a resource-rational alternative.

Just as individually learned world models can have compositional structure (i.e., decomposible into primitives, which can be recombined to plan new behaviors; Schwartenbeck et al., 2021), model-based assimilation can compositionally and selectively combine elements of one’s own world model with elements derived from social transmission. Model-based assimilation thus produces ”chimeric” representations (Cushman, 2020) that are constructed from the experiences of more than one brain, laying the basis for social recombination. Access to model-based assimilation shifts the cost-benefit calculus between different social learning pathways, not only at the level of individual strategy but also at the level of phylogenetic divergence and evolution, which we investigate next.

Links to animal behavior and cumulative culture

Here we compare humans with our best-studied close relative, chimpanzees. In particular, causal reasoning and observational learning are two domains in which they are reported to differ in their abilities. We discuss how these two domains are functionally linked through model-based assimilation, with implications for species divergence in traits like CCE.

Chimpanzees exhibit deficiencies in their understanding of causal principles that appear obvious to human adults, for example in tool use (Penn & Povinelli, 2007; Laland & Seed, 2021). Some have attributed this deficit to a more fundamental inability to enagage in compositional reasoning (Penn, Holyoak, & Povinelli, 2008). Compositional reasoning may be unique to humans (Dehaene, Al Roumi, Lakretz, Planton, & Sablé-Meyer, 2022; Sablé-Meyer et al., 2021) and may be imposing a clear limit to model-based learning in chimpanzees.

Observational learning is another behavioral domain where humans and chimpanzees qualitatively differ (Clay & Tennie, 2018; Neadle et al., 2021). Whereas chimpanzees tend to emulate behavior (copying goals, i.e., value inference), humans robustly imitate even causally irrelevant actions (Horner & Whiten, 2005). Many explanations have been proposed, ranging from the presence of pedagogy making imitation more rational for humans (Csibra & Gergely, 2009), to the possibility that imitation can facilitate subsequent causal insight (Lyons, Young, & Keil, 2007).

Hypothesis 2: Humans get more from imitation than chimpanzees. We propose that human and chimpanzee differences in causal reasoning and observational learning are functionally linked. For humans, imitation enables not only action learning but also the social transmission of causally rich world models via model-based assimilation. In contrast, chimps are limited in causal understanding and may lack the capacity to extract causal insight from imitating actions (if they could imitate well). In the absence of causal understanding, value inference (i.e., emulation) has more utility than action copying for chimpanzees, particularly for novel actions with high motor learning cost.

Humans thus benefit more from action copying, and are able to derive socially informed world models. These models undergo recombination within an interconnected population. The iterated dynamic of social transmission, recombination, innovation, and further transmission may be expected to produce novel, hybrid world models in an open-ended manner and drive population variation. Arising from a background of neural, behavioral, and cultural evolution (Uchiyama & Muthukrishna, 2022), recombinatory world models may have functioned as a key factor for human CCE.

Conclusion

We argued that imitation can support the social transmission of world models, through a pathway called "model-based assimilation", facilitating the social recombination of knowledge across multiple brains. This pathway bypasses the computational costs of explicit Theory of Mind inference, potentially explains why humans imitate while chimpanzees emulate, and may be a key factor for human cumulative cultural evolution.

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