Title

The relationship between latent state inference and (intolerance of) uncertainty

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In their review, Sandhu, Xiao and Lawson (2023) outline a framework for the study of uncertainty, particularly in the context of psychopathology. The authors correctly argue that clinically-derived intolerance of uncertainty can be better understood through a computational lens. One aspect of the proposed framework is the uncertainty about the number of latent states in the environment. This is indeed an important aspect, however, as pointed out by the authors the relationship between state inference and uncertainty extends beyond the uncertainty about the number of states. In this commentary I will briefly expand on this relationship. Specifically, I will suggest that uncertainty largely determines the process of state inference and that the desire to reduce uncertainty may lead to increased tendency to identify latent structures. I will also demonstrate with simulations the importance of taking state inference into account in computational models to dissociate its contributions from uncertainty related processes..

Identification of regularities in external environments to inform internal representations is arguably one of the key drivers of flexible behavior, as highlighted by recent work on learning and cognitive maps (Schuck et al., 2016). Consider a classic reversal learning setting, in which a cue switches repeatedly between signaling high versus low probability to receive a shock (Fig. 1a). This environment is characterized by high uncertainty. But what do participants make of this uncertainty? Many experiments have shown that participants might take the uncertainty to imply the existence of two latent states of the environment, between which one can switch, as opposed to gradually updating their expectations. Such separation of acquisition (high shock probability) and extinction (low shock probability) into separate internal states has been highlighted as a potential mechanism behind fear relapse (Gershman & Hartley, 2015), and much research and clinical practice has focused on achieving context-independent extinction (Craske et al., 2014). Recently, high trait anxiety has been associated with the tendency to infer multiple latent states during aversive probabilistic learning, potentially explaining higher rates of fear relapse in anxious populations (Zika et al., 2023). However, the ways in which state-dependent learning relates to uncertainty have not been explicitly discussed. Here, I pinpoint two ways in which uncertainty and its intolerance relate to, and interact with, inference of latent states beyond the higher order uncertainty about the number of states.

As pointed out by the authors, the two broad types of uncertainty are irreducible (i.e., first order) and reducible (e.g., second order and higher order uncertainty). Here, I argue that both of these types of uncertainty can directly drive inference about latent changes in the environment. Specifically, deciding whether a surprising outcome represents a shift in the underlying context or an oddball event depends on what our current estimates of reducible and irreducible uncertainty are. In Zika et al. for example, each state is accompanied by an estimate of uncertainty (estimate of state-specific first order uncertainty). During learning, the agent continuously monitors the magnitude of recency-weighted (unsigned) prediction errors, and infers a new state when errors have been larger than what is expected under the current state (i.e., uncertainty is reducible). Both types of uncertainty are necessary to evaluate whether the underlying state has changed. Such a nuanced way to assess uncertainty and inferring states has one core benefit: it improves predictions, and it leads to less subjective uncertainty (i.e. uncertainty experienced/perceived by the individual, which may be different from objective uncertainty and may not distinguish between different uncertainty types). This in turn raises an intriguing possibility: do individual differences in intolerance of uncertainty play a role in separation of environments into subjective states? This might explain why individuals high in trait anxiety have been reported to infer multiple latent states. While identification of existing latent structures is arguably an adaptive feature, excessive tendency to infer structure where there is none, essentially leads to overfitting of the data. This may in turn lead to increase in subjective uncertainty, resulting in a sense of feeling overwhelmed or helpless. As mentioned earlier, separation of aversive environments to multiple internal states also means that past aversive memories are not forgotten and can return in future.
Importantly, due to the inherent interdependence between the two uncertainty types, bias in one mechanism would also lead to biases in others, and it may not be clear whether abnormal learning is due to mis-estimation of reducible or irreducible uncertainty.

Additionally, incorporating state inference into models of learning under uncertainty may be important for correct identification of uncertainty-related mechanisms. Here, I will focus on two aspects: analysis of learning rates and estimation of stochasticity. First, a number of studies have found altered aversive learning rates in clinical populations (e.g., autism, anxiety; Browning et al., 2015; Huang et al., 2017; Lawson et al., 2017). Intriguingly, change of learning rates may reflect a number of separable cognitive mechanisms such as mis-estimation of a specific type of uncertainty. Importantly, it can also reflect increased reliance on state inference, even in cases where no trial-by-trial learning takes place To demonstrate this point, we generated artificial data using a weighted mixture of predictions of of Rescorla-Wagner model (with fixed learning rate of 0.1) and a state inference-like mechanism (SI), systematically varying the contributions of the two (for simplicity, here the SI learner knows that there are two states). We then estimated the resulting learning rates. Indeed, increasing the proportion of the state inference model led to elevated learning rates. Similarly, contributions of a volatile learner (Pearce-Hall, version from Li et al., 2011) resulted in a comparable increase in estimated learning rates (Fig. 1b). This is particularly important considering that some of the work on

volatility has employed tasks with structured reversals to induce volatility, effectively conflating volatility with state inference (as also pointed out by the original authors). Note that the chosen baseline learning rate (alpha=0.1) means that we observe elevation of subsequent alphas, however, if the baseline learning rate were high we would see relative decrease (see also Nassar & Troiani, 2021). The main point however stands: fast one-state learning and two-state switching lead to the same relative change in learning rates. Dissociating the two mechanisms is important to understand the subjective experience - while a participant with high volatility estimate will find themself in a state of high subjective uncertainty, an individual who has inferred the latent structure will have arguably reduced some of the environmental uncertainty, and may in turn be experiencing a state of low(er) subjective uncertainty.
Second, recent work focussing on the role of uncertainty in anxiety has suggested that highly anxious individuals tend to mis-estimate stochasticity (Piray & Daw, 2021). In their simulations the authors show that stochasticity-lesioned model performs abrupt jumps when contingencies change, similarly to a state-inferring model. We demonstrate this general pattern in Fig. 1c. In order to dissociate whether a participant mis-estimates stochasticity or relies on state inference, a model incorporating both mechanisms can be used. Additionally, in paradigms employing single-trial expectancy ratings (e.g. cannonball task), dissociating the two mechanisms can be achieved by analyzing learning during oddball events (red circles in Fig. 1c). Specifically, participants who misestimate stochasticity should show learning from oddball events while participants aware of the current state should show relatively little learning (see also Yu et al., 2021 and Zika et al., 2023).

In summary, we argue that state inference is closely intertwined with uncertainty. Specifically, state inference is directly informed by irreducible and reducible uncertainty, and tendency to infer states may be driven by intolerance of uncertainty. Additionally, state inference can sometimes lead to similar behavioral predictions as uncertainty-based mechanisms. Therefore, incorporating it into models of learning under uncertainty is warranted. This is particularly important in the context of psychopathology where omission of state inference can lead to misinterpretation of results relating to subjective uncertainty.

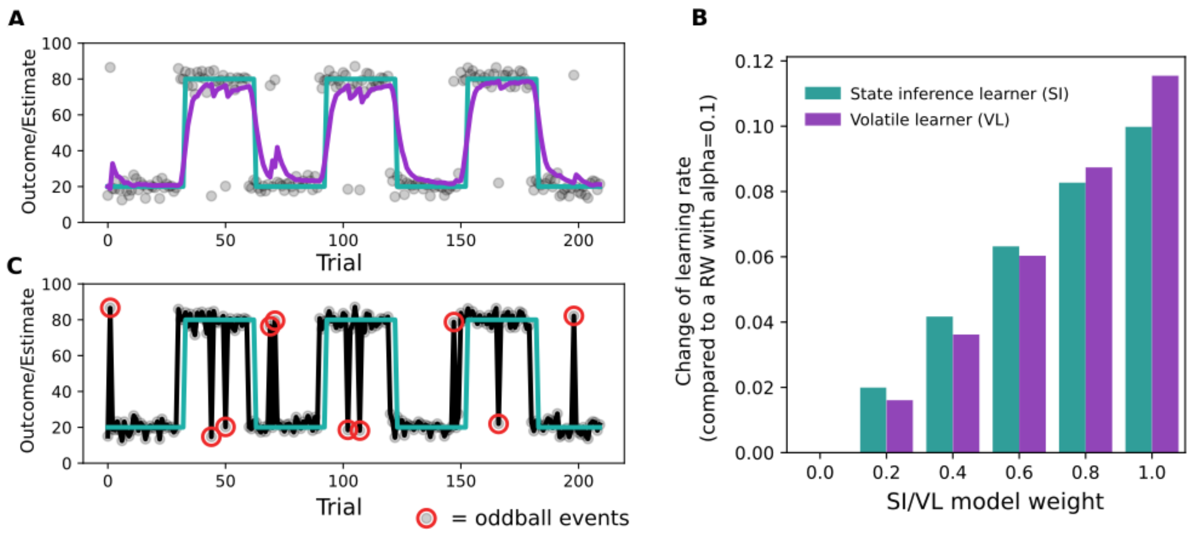

Figure 1 *Panels (**a**) and (**c**) represent simulated time courses of different theoretical agents. The gray dots represent outcomes received on each trial (e.g., reward or shock level). The lines represent trial-by-trial predictions generated by each model given the outcomes. (**a**) Simulated time-courses of predictions of a volatile one-state learner (purple) and a two-state switching model (teal). (**c**) Simulated time-courses of predictions of an agent which mis-estimates stochasticity (i.e., fully learns from all events; black) and a two-state switching model (teal). Red circles highlight oddball events where predictions of the two mechanisms diverge: while both mechanisms are characterized by large switches following a reversal, the state-inferring model tends to ignore single oddball events because they are likely rare uninformative events. At the same time, the stochastic agent learns from all events equally, including oddballs. (**b**) Learning rates estimated by a Rescorla-Wagner (RW) model fitted to data with increasing contributions of either volatile learner (VL) or state inference learner (SI) models. The predictions on each trial were mixed using a weighted sum of RW (alpha=0.1) and VL/SI. Increasing the weight of VL/SI resulted in increased learning rates in both cases. Y-axis shows the change in estimated learning rate over a RW model with alpha=0.1, i.e., a model with 0 weight on either SI or VL models will just be the baseline RW model.*

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