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Learning how to reason and deciding when to decide

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Abstract

Research on human reasoning has both popularized and struggled with the idea that intuitive and deliberate thoughts stem from two different systems, raising the question how people switch between them. Inspired by research on cognitive control and conflict monitoring, we argue that detecting the need for further thought relies on an intuitive, context-sensitive process that is learned in itself.

Research on reasoning about moral dilemmas or logical problems has traditionally dissociated fast, intuitive modes of responding from slow, deliberate response strategies, often referred to as System 1 versus System 2. For example, when deciding to take the plane versus train, our System 1 might make us decide to take the former because of its speed, while our System 2 could lead to deliberations on its environmental impact and decide for the train. De Neys (in press) proposes a new working model wherein both intuitive and deliberate reasoning are thought to originate from initial "System 1"-intuitions whose activations build up over time and potentially trigger an uncertainty signal. When this uncertainty signal reaches a certain threshold, it can trigger the need for deliberate reasoning, upon which deliberate thought or "System 2", is called upon to further resolve the reasoning problem. Here, we question the need for assuming a separate, deliberate system, that is activated only conditional upon uncertainty detection. While we are sympathetic to the idea that uncertainty is being monitored and can trigger changes in the thought process, we believe these changes may result from adaptations in decision boundaries (i.e., deciding when to decide) or other control parameters, rather than invoking qualitatively different thought strategies.

Research on cognitive control often focuses on how goal-directed control processes can help us correct, inhibit, or switch away from interfering action tendencies, such as those originating from overtrained associations (Diamond, 2013; Miller & Cohen, 2001). For example, when deciding between the train or plane, our prior habit of taking the plane might

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trigger the same decision at first, while our current goal to be more environment-friendly should lead us to the train. Importantly, recent theories on cognitive control have emphasized how these goal representations and control processes should not be considered as separate "higher" order processes studied in isolation, but that they are deeply embedded in the same associative network that hosts habits and overtrained responses. That is, goals and control functions can be learned, triggered, and regulated, by the same learning principles that govern other forms of behavior (Abrahamse et al., 2016; Braem & Egner, 2018; Doebel, 2020; Lieder et al., 2018; Logan, 1988). For example, much like the value of simple actions, the value of control functions can be learned (Braem, 2017; Bustamante et al., 2021; Grahek et al., 2022; Yang et al., 2022; Otto et al., 2022; Shenhav et al., 2013). This way, similar to De Neys' suggestion that we can learn intuitions for the alleged System 1 and 2 responses (or habitual versus goal-directed responses), we argue that people also learn intuitions for different control functions or parameters (see below).

One popular way to study the dynamic interaction between goal-directed and more automatic, habitual response strategies is through the use of evidence accumulation models. In these models, decisions are often thought to be the product of a noisy evidence accumulation process that triggers a certain response once a predetermined decision boundary is reached (Bogacz et al., 2007; Ratcliff et al., 2016; Shadlen & Shohamy, 2016). However, this accumulation of evidence does not qualitatively distinguish between the activation of intuitions versus goal-directed or "controlled" deliberation. Instead, both processes start accumulating evidence at the same time, although potentially from different starting points (e.g., biased towards previous choices or goals) or at different rates (e.g., Ulrich et al., 2015). Depending on how high a decision maker sets their decision boundary, that is, how cautious versus impulsive they are, the goal-directed process will sometimes be too slow to shape, or merely slow down, the decision. These models have been successfully applied to social decision making problems (e.g., Hutcherson, Bushong, & Rangel, 2015; Son, Bhandari, & FeldmanHall, 2019).

In line with the proposal by De Neys (in press), we agree that competing evidence accumulation processes could trigger an uncertainty signal (e.g., directional deviations in drift rate), once uncertainty reaches a certain threshold, similar to how it has been formalized in the seminal conflict monitoring theory (Botvinick et al., 2001), on their turn inspired by Berlyne (1960). However, in our view, the resolution of said signal does not require the activation of an independent system but rather induces controlled changes in parameter settings. Thus, unlike activating a System 2 that provides answers by using a different strategy, cognitive control changes the parameters of the ongoing decision process (for a similar argument, see Shenhav, 2017). For example, it could evoke a simple increase in decision boundary, allowing for the evidence accumulation process to take more time before making a decision (e.g., Cavanagh et al., 2011; Frömer & Shenhav, 2022; Ratcliff & Frank, 2012). The second-order parameters that determine these adaptive control processes (e.g., how high one's uncertainty threshold should be before calling for adaptations, or how much one should increase their boundary) do not need to be made in the moment, but can be learned (e.g., Abrahamse et al., 2016).

Although we focused on the boundary as closely mapping onto fast and slow processing, we believe other process parameters can be altered too. For example, the response to uncertainty may require or could be aided by directed attention (Callaway, Rangel, & Griffiths, 2021; Jang, Sharma, & Drugowitsch, 2021; Smith & Krajbich, 2019), the memory of previous computations (Dasgupta & Gershman, 2021), learned higher-order strategies (Griffiths et al., 2019; Wang, 2021), or the parsing of a problem into different (evidence accumulation) subprocesses (Hunt et al., 2021). Moreover, a decision maker might even mentally simulate several similar decisions to evaluate one's (un)certainty before making a response (e.g., by covertly solving the same problem multiple times, Gershman, 2021). In sum, we argue that both intuitive and deliberative reasoning result from similar evidence accumulation processes whose parameter adjustments rely on immanent conflict monitoring and the learning from previous experiences.

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