Emotions as computational signals of goal error

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Abstract:

In this chapter we argue that emotion can be viewed as an informationally rich error signal that assists agents in achieving goal states. When agents make decisions, they select actions that maximize the benefits while minimizing costs of outcomes with respect to goals. In our framework, emotions serve as sensors that transduce progress towards a superordinate goal into a feeling state. We contend that these feeling states occur not only during the receipt of an outcome, but can be anticipated and read out at the time of a decision - a process akin to temporal difference learning. However, this prospective simulation process can be noisy, particularly when predicting an outcome with which we've had minimal prior experience. To support our argument, we discuss how the feelings of regret and guilt aid in making decisions that are consistent with our broader goal states.

Emotions are a composite of various inter-related processes (e.g., autonomic arousal, expressive behavior, action tendencies, interoception, and conscious evaluations) that orchestrate adaptive responses critical for survival and well-being. Similar to the somatovisceral sensations that signal internal homeostatic goal states such as hunger, thirst, and sleep (1), emotions provide motivational signals that guide us to approach resources, avoid harm (2), and navigate the complexities of the social world (3-5). In this chapter we explore how these motivational signals can be formalized as "goal errors," which influence how we make decisions.

Decision-making can be defined as selecting a strategy, policy, or action that best maximizes the anticipated outcome of a value function, while minimizing the costs with respect to a particular goal. Value functions are often based on expected utility theory (6), which provides a set of mathematical axioms that define rational choice. Though considerable work has demonstrated that the axioms of expected utility theory do not always adequately describe behavior (7, 8), this framework continues to provide a useful first order approximation of how we can mathematically describe value functions.

There are several ways in which emotions have been thought to influence decision-making (9, 10). First, emotions can modulate value signals by changing the salience or attractiveness of a given option (11). For example, when the affective intensity of an outcome becomes quite large, such as an opportunity to win a European vacation or receive a painful shock, people tend to overweight low probabilities of occurrence and underweight high probabilities when making a decision (12). Second, emotions can also serve as independent value signals in the utility function. These motivational value signals can take the form of *expected* or *immediate* emotions. Expected emotions refer to anticipated emotional states associated with a given outcome such as regret (13) or guilt (3). Immediate emotions, on the other hand, are experienced at the time of decision and occur either directly in response to a specific event (e.g., anger or fear (4, 14)) or as a result of a transitory fluctuation in mood (15-17).

Models of Emotion & Decision-Making

Early theories sought to explain the influence of emotion on decision-making from cognitive and neural perspectives. Appraisal models describe emotion as a sequence of context-dependent processes from perception to action (18-20). These models describe discrete emotions as arising from a combination of cognitive evaluations (21) that occur at differing time scales (19). This perspective has been very amenable to computational modeling and has been adopted by psychologists (22), computer scientists (23), economists (1, 24, 25), and neuroscientists (26, 27). One key idea that stems from this theoretical tradition is that feelings provide a source of information that can directly influence value functions. While this hypothesis has evolved over the years, e.g. "affect as information" (28), "risk as feelings" (29, 30), the “affect heuristic” (11), and the "somatic marker hypothesis" (26, 27), its central ideas have found consistent support from cognitive neuroscience. For example, the ventromedial prefrontal cortex (VMPFC) is critical for integrating reward (31) and affective value (32), the insula in reading out somatovisceral states (33-35), and the amygdala in directly linking cognitive and perceptual processes to arousal responses (36, 37). Lesions to each of these regions impair how emotions influence decision-making, by rendering critical information largely unavailable (26, 35, 38, 39).

Another contribution, central to this framework, is the idea that feelings arise not only from direct evaluation of the environment, but also from the prospective simulation of feelings given particular outcomes. Much work has attempted to model these anticipated feelings into the decision-making process itself. For example, Regret Theory attempts to directly model the appraisal of how we might feel if we found out that we could have made a better decision (40, 41). Other frameworks, such as Psychological Game Theory, directly model belief-dependent psychological payoffs into utility functions (42, 43). These types of approaches make it possible to incorporate more sophisticated social preferences such as intention-based fairness (44, 45) and belief-dependent emotions, such as guilt-aversion, (24, 46, 47) into models of decision-making. One such early attempt, modeled decisions in terms of anticipated pleasure states ("decision affect theory") and impressively explained about 55% of the variance in choice behavior (48, 49). Thus, anticipated affective states play an important role in how we make decisions.

Error Signals

Here we conceive of emotions as an error signal based on the distance between the current state and a superordinate goal. This conceptualization borrows from control theory (50), casting emotions as "sensors" that provide a prediction error signal for the controller to make adjustments to the system. For example, consider how a thermostat works. An agent sets a goal temperature, say 70 degrees Fahrenheit, and the thermostat reads out the current temperature from the thermometer sensor. The decision policy for the thermostat is to turn on the heat if the error function is negative (i.e., turn heat on if (Goal temperature - Current temperature) < 0). This simple prediction-error based computational algorithm (51, 52), has received considerable attention in understanding how value is represented in the context of learning and decision-making. For example, seminal work by Montague, Dayan, and Schultz (53, 54) demonstrated that dopamine neurons located in the ventral tegmental area (VTA) behave consistently with the principles of temporal difference learning (52) and increase their firing rate following unexpected rewards proportional to the degree of prediction error. Importantly, as the agent learns to associate a cue with an outcome, the reward expectation signal appears to propagate backwards in time to any cue predictive of the reward (Figure 1A). Thus, after an agent has learned the contingencies of a cue-outcome relationship, dopamine neurons in the VTA (53) and nucleus accumbens (55-57) will fire at the time of the cue, and not at the time of the reward (if the outcome was perfectly predicted).

In this way, temporal difference learning provides a computational operation, which allows agents to achieve a goal state that maximizes reward. However, agents have many additional goals (e.g., making the best decision, and minimizing harm to others) and we believe there are analogous prediction error signals for each of these goal states formalized as anticipated affective reactions (e.g., regret and guilt).

[Insert Figure 1 about here]

Regret

One critical goal for all agents is to maximize the likelihood that the optimal policy is selected. If an agent makes a decision that turns out to have an unfavorable outcome, they will most likely feel disappointment. However, if an agent makes a decision and learns that they could have made an even better decision regardless of outcome favorability, they will feel regret (40, 41). Therefore, regret can be viewed as an affective error signal of a suboptimal choice resulting from the comparison of a decision-outcome, with a counterfactual outcome had another action been taken.

Similar to reward prediction error described above, regret occurs at the time of feedback. However, agents can also anticipate how bad they would feel if they selected a suboptimal decision during the decision period, an effect termed 'regret-aversion'. For example, consumers become more regret averse when asked to consider possible decision errors. They are less likely to wait for a better possible future rebate when purchasing a car, and select safer name-brand products than less expensive lesser-known products (58). The experience of regret appears to be influenced by at least two components, comparative evaluation of counterfactual outcomes, and agentic responsibility associated with having made a suboptimal choice (59, 60). Interestingly, errors of commission appear to be associated with regret in the short-term, but errors of omission are associated with more regret in the long term (61).

Several studies from cognitive neuroscience have helped to further elucidate the role of regret as an error signal in decision-making. The VMPFC appears to play a critical role in both the experience and anticipation of regret (62). BOLD fMRI activity in the VMPFC is correlated with regret signals in gambling tasks, and over time there appears to be an anticipated regret signal in the medial orbitofrontal cortex OFC that tracks regret-aversion (13). Lesions to the orbitofrontal cortex appear to impair the capacity to both experience regret and also avoid it when making decisions under uncertainty (63).

Regret does not appear to be solely a human experience either. Several studies have illustrated that non-human primates can learn from counterfactuals (64, 65) and more recent work has demonstrated that rats appear to show behavioral indicators of regret that are dissociable from disappointment and correlated with increased firing of OFC neurons (66). Interestingly, regret is not only an important signal for multiple species of animals, but has also become a powerful algorithm in computer science applications. Such 'no-regret learning' or 'regret-matching' algorithms update strategies based on how each strategy would have performed in the last iteration of a game and can be used to solve computationally intensive games such as heads-up no hold-em' poker (67). These kinds of diverse findings provide convergent evidence as to how regret is an informationally rich signal that motivates agents to make the best decision from the available choice set.

Guilt

Another important goal for agents as they navigate the social landscape is to minimize harm to others. Guilt occurs in these interpersonal contexts when one believes that they have harmed or disappointed a relationship partner (68). Guilt has been considered a prosocial emotion in that agents have a tendency to take actions that repair the relationship following transgressions (69). However, guilt can also be anticipatory and promote cooperation through simulating the act of committing a transgression. Thus, similar to regret, future experiences of guilt associated with a given choice can be anticipated by calculating a counterfactual comparison of another agent's outcomes. Psychological game theory (42, 43) provides a method to incorporate both material payoffs, and belief-dependent psychological payoffs, into an agent's utility function. This innovation critically provides a way to mathematically formalize emotions like guilt (24, 47) and can dramatically improve game theoretic solution concepts (i.e., behavioral predictions).

For example, consider a Trust Game based on (47) depicted in Figure 1C. Player P_1 is endowed with $1 and can keep it by choosing 'Out' or can invest it by choosing 'In'. Investments are multiplied by a factor of 4 and P_2 then chooses whether to 'Share' and split the multiplied investment evenly or 'Keep' all of the money. Guilt-aversion predicts that if P_2 is sensitive to guilt, choosing 'Keep' will result in a negative psychological payoff proportional to the degree to which they believe they let down P_1. That is, their utility decreases by their second order belief Φ'', defined as P_2's belief about P_1's belief about Φ: the probability of P_2 choosing 'Share'. If P_2 is solely motivated by monetary payoffs, then the game-theoretic solution is choosing 'Keep' and receiving the largest possible material payoff. However, if P_2 is guilt-averse ($\Theta > 1$), then the game-theoretic solution is choosing 'Share' and avoiding a negative psychological payoff.

Empirical studies utilizing such trust games have found that P_2s return a greater percentage of money when they believe P_1s are more trusting and have a higher expectation that they will choose to share (3, 46, 70-72) (but see (73, 74) for alternative accounts). Additionally, two studies to date have attempted to elucidate the neural substrates of guilt-aversion while P_2 decides whether or not to honor their partner's trust. Chang et al., (3) elicited P_2's second order beliefs about the amount of money they believed their partner expected them to return, and compared trials in which participants chose a strategy that minimized guilt-aversion to trials in which they chose a strategy that maximized self-interested. Participants had increased activity in the insula, anterior cingulate cortex (ACC) dorsolateral prefrontal cortex (DLPFC) and temporoparietal junction (TPJ), a network that is thought to be involved in processing negative affect, salience, cognitive control and theory of mind, when they behaved in accordance with guilt-aversion. In contrast, when participants behaved in accordance with maximizing monetary outcomes, they had increased activation in the ventromedial prefrontal cortex (VMPFC), ventral striatum, and dorsomedial prefrontal cortex (DMPFC), regions consistently involved in reward processing and mentalizing. This study was recently replicated using a slightly different design (72). In this study, the payoff matrix was constructed to dissociate reward value, inequity-aversion, and guilt-aversion. The authors found that guilt-aversion correlated on a trial-to-trial basis with activity in the right DLPFC controlling for reward magnitude and the amount of inequity in each players' payoffs. Importantly, in a follow up study, these researchers found behavioral evidence suggestive of the DLPFC's causal role in guilt-aversion by increasing neuronal excitability with anodal transcranial direct current stimulation relative to a sham control condition. Together, these studies show that the anticipation of guilt is associated with negative error signals when the goal is to minimize harm to others and associated with increased activity in the insula, DACC, and DLPFC.

Affective Forecasting Errors

A central component to making an optimal decision in the ways discussed above is the simulation process whereby an agent tries to predict a future feeling state. Because these anticipated feelings are the result of cognitive simulations, they may not necessarily reflect the *precise* feelings of an experienced emotion. While the majority of such "affective forecasts" are generally accurate, individuals are also prone to exhibiting systematic mispredictions of their own emotions (75, 76). These mispredictions typically reflect inaccuracies in anticipated intensity and duration, rather than the direction (valence) or type of experienced emotions (77). These mispredictions can be viewed as distortions of the simulation process, primarily occurring as a consequence of neglecting the influence of additional factors occurring both in the future, and at the time of the decision (76).

For example, when individuals underestimate the intensity or duration of future emotions, they frequently underweight the effect of visceral feelings, in essence, projecting current emotional information onto simulated future feeling states (1). These "empathy gaps" occur in numerous contexts such as shopping for food while hungry, which can result in purchasing additional unintended food items (78), overweighting current hunger and thirst states when planning for a hike (79), or in-the-moment arousal leading to an increased willingness to endorse riskier future sexual behavior (80).

Even more pervasive, individuals tend to overweight the impact of future events and the resultant positive and negative emotions (77). This impact bias is ubiquitous to a variety of situations and individuals ranging from the prediction of overly negative feelings from an unwanted pregnancy, positive HIV test result or receiving pain, to overly positive feelings from winning the lottery or losing weight (81-83). Furthermore, these strong affective outcomes appear to disrupt how people weight the probability of the event occurrence (11, 12). During these types of simulations individuals ignore critical contextual and situational factors, such as surrounding social circumstances, instead focusing on the occurrence and affective value of single isolated events (84, 85)

Research suggests several potential reasons why these affective forecasting errors might occur (86). First, emotions are notoriously difficult to both define and measure and there is large intra- and inter-individual variability in the experience of emotions. For example, there do not appear to be any consistent signatures of subjective ratings, physiological measurements, or neural representations for discrete emotions (87). In addition, measurements are likely highly influenced by how the question is framed (88) and also measured (89). Second, as emotions appear to have multiple interacting components (e.g., physiological responses, interoception, appraisal, action tendencies), it is unclear how well we can access and synthesize all of these components when asked to report these feelings in terms of a verbal description or numerical intensity (90). We likely have a poor ability to read out somatovisceral states and accurately translate these feelings into verbal descriptions (91). This is evidenced by our inability to use somatovisceral representations when remembering and prospecting a pain experience (1). Third, many affective forecasting errors occur for events with which we typically have limited experience. For example, most people do not have repeated experiences of winning the lottery or contracting HIV. Most likely, if we did experience these events multiple times, we would be able to more accurately predict how we would feel in response to these events and rely less on using essentialized prototypes of these experiences (86).

Conclusion - Emotions as goal error

In this chapter, we have discussed how emotions such as regret and guilt can be formalized as appraisals by incorporating belief dependent payoffs into expected utility theory. Importantly, agents receive negative psychological utility from experiencing these emotions and are motivated to make decisions that minimize their occurrence. Both regret and guilt can be conceptualized as errors to the respective superordinate goals of making the best possible decisions and minimizing harm to others. A key tenet of this hypothesis is that agents can successfully forecast their future affective states. While we have discussed evidence suggesting that people have systematic biases when simulating future affective states, most of these studies have examined single emotional events, with which individuals may have had limited experience (e.g., winning the lottery). It remains an open question about what happens when agent has repeated experiences with the same outcome. According to the process of temporal difference learning outlined above, agents should learn to accurately anticipate the emotion associated with an outcome and make a decision that acts to minimize its future experience. Thus, from this perspective, emotions serve as a learning signal to update beliefs about the world and aid in selecting decision policies that maximize attaining specific goals. There is preliminary evidence supporting this hypothesis. Coricelli et al. (13) observed that when making repeated independent decisions under uncertainty, most participants changed their behavior over the course of the experiment to become more regret-averse. One of the critical predictions of our hypothesis is that as an anticipated emotion becomes better predicted, the experience of that anticipated emotion will become more intense at the time of the decision, and agents will become more satisfied with their decisions as a consequence. We look forward to seeing future work testing the tenets of this computational theory.

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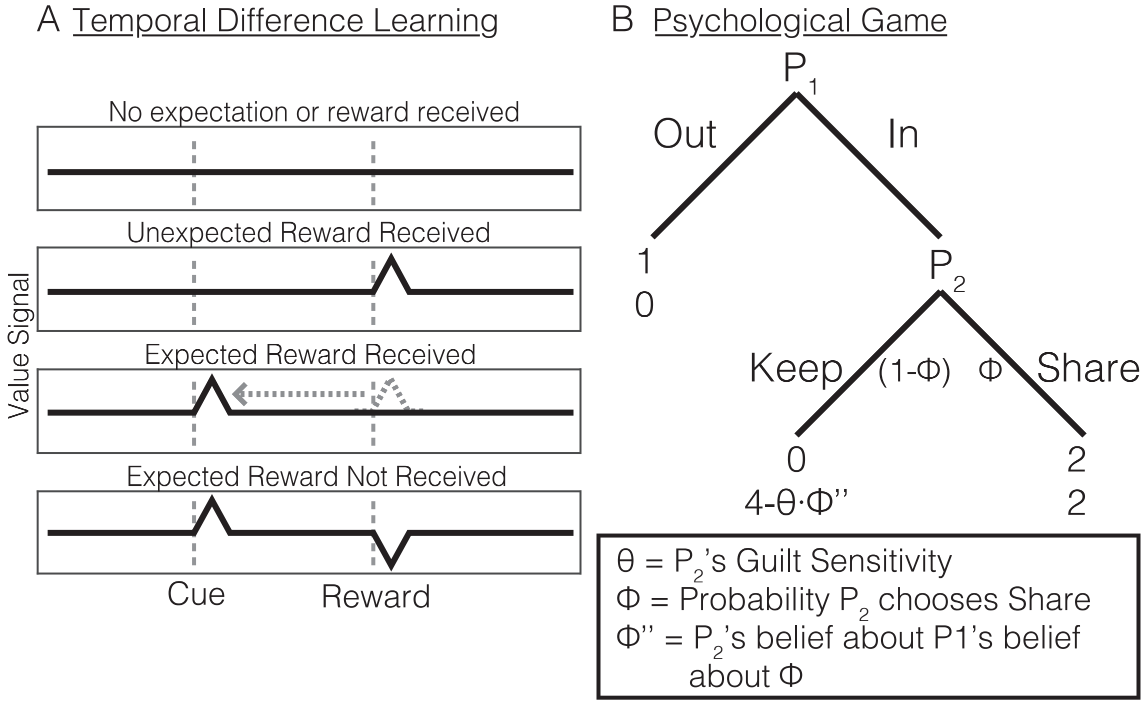
Figures

Figure 1. Prediction Error



Panel A shows a hypothetical value signal based on predictions of temporal difference learning (53). There is no value signal when there is no expectation or receipt of reward. When an agent receives an unexpected reward, they receive a value signal, which back propagates to the predictive cue. When an agent expects a reward and receives it, their value signal occurs at the time of expectation and not receipt. However, if the agent expects a reward and does not receive it, they will experience a negative value signal. Panel B depicts a Trust Game with psychological and material payoffs based on (47). P_1 is endowed with $1 and can choose "In" or "Out". If they choose "In" the endowment is multiplied by a factor of 4 and P_2 then decides whether to "Share" and split the money or "Keep" all of the money to themselves. P_2 will receive both material and negative psychological payoffs if they select "Keep" based on their second order belief about what they think P_1 expects them to do scaled by their sensitivity to guilt.

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