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Computational neuroscience approaches to social cognition

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How do we form impressions of people and groups and use these representations to guide our actions? From its inception, social neuroscience has sought to illuminate such complex forms of social cognition, and recently these efforts have been invigorated by the use of computational modeling. Computational modeling provides a framework for delineating specific processes underlying social cognition and relating them to neural activity and behavior. We provide a primer on the computational modeling approach and describe how it has been used to elucidate psychological and neural mechanisms of impression formation, social learning, moral decision making, and intergroup bias.

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How do we form impressions of other people? Is Jane kind? Do we like her? And can we predict how she will act? These are core questions of social cognition—the field of psychology devoted to understanding the processes through which we perceive, represent, and act towards persons and groups. Social psychologists have pursued these questions for over 40 years, and the earliest social neuroscience studies probed the neural basis of impression formation and social attitudes. Recently, social neuroscientists have used computational approaches to advance and, in some cases, reconceptualize thinking on social cognition. Here, we provide a brief introduction to the computational modeling approach and highlight recent studies that have used it to elucidate social cognition.

Computational modeling approaches to social cognition and social neuroscience

The central aim of social cognition is to understand social behavior by elucidating its underlying cognitive and neural mechanisms. In the past, this was accomplished with careful experimentation and behavioral modeling (e.g. Process Dissociation, Quad Model) [1,2], but these approaches are limited in their ability to assess complex dynamic processes. Computational models allow researchers to probe trial-by-trial dynamics of learning and choice and to make precise quantitative predictions about behavior across time (Box 1). In neuroimaging research, computational models permit researchers to test neural correlates of theorized latent variables that are not directly observable in behavior. For example, in models of reinforcement learning, a key variable is *reward prediction error*—the discrepancy between the reward one receives and the reward one expected (see Box 1) [3]. By fitting behavior to reinforcement learning models, researchers can estimate a learner's trial-by-trial prediction errors. Fitting this timeseries to fMRI data can then identify neural regions that covary with prediction errors.

Formal models also permit researchers to compare human behavior to that of an optimal agent. For example, by comparing behavior and neural responses to a Bayesian model, one can ask whether people conform to rational principles of updating in social settings [4,5•] or deviate from rationality in systematic ways [6]. Such deviations may provide important clues to psychological and neural processes involved in behavior. Alternatively, with agent-based modeling, researchers can simulate agents that instantiate different models and identify which performs best in a given task (e.g. achieving the highest accuracy or winning the most money) [7••].

Neuroimaging provides clues about the cognitive processes that drive a behavior, and formal models offer a powerful approach to more precisely delineate such processes. For instance, people with stronger racial bias learn more readily to avoid threatening out-group faces [8]. This bias could emerge because they evaluate the faces more negatively (*differential evaluation*) or because they learn more efficiently (*differential learning*). Computational modeling supports the second explanation, providing insight into how social biases shape learning itself [8]. When combined with neuroimaging, formal models can identify dissociable patterns in neural activity, adding further precision in characterizing neurocognitive substrates of social behavior. Although one can never know whether one's theoretical account is the true explanation,

Box 1 A reinforcement learning modeling primer

Computational models provide an abstract mathematical description of how one might learn or make choices. Here, we offer a brief primer on *reinforcement learning* (RL) models, which have been influential in social neuroscience, although Bayesian and drift-diffusion models are also widely used.

RL models describe how an agent forms action preferences through trial and error. For instance, imagine choosing between two slot machines to earn money. Initially, you might choose randomly. As you win money, you form and update expectations about their respective payouts. In RL models, this update relies on a *reward prediction error*, or the difference between the reward one received and the reward one expected (symbolized δ):

$$\delta_t = Reward_t - Q_{t-1} \tag{1}$$

Here, Q_{t-1} represents the expected reward value as of the previous time point. Prediction errors are used to update one's previous estimate of reward upward or downward:

$$Q_t = Q_{t-1} + \alpha\delta_t \tag{2}$$

where α is a free parameter representing a learning rate. This parameter scales prediction errors and therefore controls the extent to which one updates expectations. With a learning rate of zero, agents would not update their expectations at all; with a learning rate of one, agents would fully update their expectations based on prediction errors.

Finally, an agent makes a choice on the subsequent trial, given the updated values of the slot machines. This is frequently modeled using a 'softmax' equation:

$$p_i^t = \frac{\exp(\beta \times Q_{i,t})}{\sum_j \exp(\beta \times Q_{j,t})} \tag{3}$$

where β is a parameter controlling stochasticity of choice, and $p_{i,t}$ is the probability of choosing option i (of j options) on trial t. This equation indicates that participants will probabilistically choose an option based on the difference in expected reward between them. Eq. (3) can be replaced with a linear function to model responses like reaction time [15] or skin conductance response [69].

Together, these equations specify how an agent learns which action to take through trial and error. Given a set of parameters α and β, these equations make quantitative predictions about how likely an agent would be to choose each option on each trial. Computer programs can find parameter values that maximize the match between predicted choices and actual choices. Moreover, alternate models can be specified and compared to see which provides the best match (for details, see Ref. [70]).

Finally, given best-fitting parameters, one can estimate the expected value or prediction error experienced by an agent on every trial during choice and feedback, respectively. This timeseries can serve as a regressor in fMRI analyses, identifying regions that show greater fMRI signal during trials with greater value or prediction error signals.

modeling can identify the best account among competing models (see also Refs. [9,10•]).

Contributions of computational approaches to social cognition & social neuroscience

Here, we review notable areas of innovation in computational social neuroscience, with special attention to the advantages described above: dissociating component processes, linking latent variables to the brain, gaining quantitative precision, and comparing behavior to optimality.

Social reinforcement learning

Humans tend to repeat actions that yield reward—a process known as reinforcement learning [3,11–13]. In non-social tasks (e.g. winning money from a slot machine), neural activity in ventral striatum correlates with reward prediction errors specified by computational models of reinforcement learning [14] (see Box 1). Computational studies reveal that similar processes also underlie social reinforcement learning, across behavior and the brain. First, social rewards—including smiling faces, social conformity, positive evaluations, and vicarious gains—can reinforce behavior in the absence of monetary reward [15–21]. Second, reward reinforcement processes can support the formation of social attitudes [22–24]. For example, when someone buys us lunch or pays a compliment, this rewarding feedback can encourage future interactions with that partner [7••]. Both kinds of social learning have been linked to reward prediction errors in ventral striatum, suggesting that similar computations underlie social and non-social reinforcement (but cf. Refs. [20,25,26].). As such, principles of reward learning can be brought to bear on sociocognitive questions, offering novel predictions about how people develop complex social attitudes and preferences [27•,28].

By comparison, traditional social psychological theories assume that attitudes are formed through passive observation of positive or negative information about a person and represented in a conceptual network [29,30]. The emerging evidence from reinforcement modeling suggests that these modes of attitude formation—conceptual and instrumental—may be complementary, and that each type of representation may support different aspects of attitude expression (e.g. in judgments and impressions as opposed to choice behaviors) [29]. Hence, a computational modeling approach promises to further illuminate the psychological mechanisms involved in the formation of social attitudes and preferences.

Impression formation

Computational models are shedding new light on how people update impressions over time. Prior fMRI investigations revealed that impression updates are associated with activity in a broad set of cortical regions, including dorsomedial prefrontal cortex (dmPFC), inferior parietal lobule (IPL), ventrolateral prefrontal cortex (vlPFC), and posterior cingulate cortex (PCC) [31–34]. These activations may reflect prediction errors related to the traits of others—that is, the discrepancy between a person's behavior and the behavior one expected based on a trait impression (e.g. of competence [6,35], generosity [7••,36], or trustworthiness [4,37–40]).

Computational studies suggest that distinct brain regions track two types of trait prediction errors. First, when observing others, people can update a conceptual representation of others' traits. Therefore, some studies have examined *absolute prediction errors*, or overall surprise, when people observe another's behavior—for instance, learning a target was more *or* less generous than expected [35,36]. These prediction errors correlate with cortical regions including those listed above. Second, when directly interacting with others, one can update value representations informed by another's traits, such as inferring that a generous person is a valuable interaction partner. Another line of work has therefore examined *directional prediction errors* during interaction, such as learning that a partner was more generous than expected [7••]. These prediction errors correlate with activity in ventral striatum—a region associated with reward and valuation—in addition to cortical regions noted above (Figure 1). Together, these studies reveal distinct ways in which the brain tracks the traits of others—one that may build a conceptual representation of others and one that may track the value offered by a partner's traits. In doing so, this work again expands the scope of social cognition to include impression formation through active social interaction and value-based learning.

Bayesian models may further reveal whether people update impressions in an optimal manner [4,6,7••,41]. For instance, Bayesian models specify how quickly a learner should revise prior beliefs in light of new evidence: in a *volatile* environment (featuring rapid change), one should update beliefs quickly in light of new evidence, whereas in a *stable* environment, one should update beliefs more slowly [42]. When learning about another person's trustworthiness, perceivers track the person's volatility and update impressions quickly or slowly as a result [4,41]. These estimates of volatility correlate with activation in the anterior cingulate cortex (ACC) gyrus [4]. Bayesian models can thus identify psychological and neural processes required for optimal impression updating.

By the same token, Bayesian models can reveal illuminating deviations from optimality. For example, when people learn about an advisor's competence, their judgments do not mimic an optimal Bayesian learner; instead, people show confirmation bias by down-weighting negative outcomes, thus maintaining unrealistic optimism about another's competence [6]. By providing a benchmark for rationality, Bayesian models can thus identify biases in impression updating.

Mentalizing

Social decisions often require a consideration of others' mental states. For instance, playing chess, giving gifts, and offering condolences require us to consider the intentions, preferences, and emotions of others. Computational studies characterize how people update their inferences about mental states and translate these inferences into choices. In the context of economic games, in which participants must often cooperate or compete with others, computational models specify how people update beliefs about the actions a competitor will take [43], try to influence others [44,45••] or reason about another's strategy [46].

Computational approaches can also address how we become more accurate in inferring others' mental states over time, such as learning that a friend often appears calm even when upset. This process can be modeled as a type of reinforcement learning: as people make judgments and receive feedback, they adjust their inferences by giving more or less weight to helpful or unhelpful cues (e.g. a calm facial expression) [47•]. Indeed, during feedback, reward prediction errors related to accuracy were found to correlate with ventral striatum activity. In contrast to traditional social psychological approaches employing single-shot judgments, this work suggests that people value social accuracy and improve their mental state inferences over time through reinforcement.

Observational learning

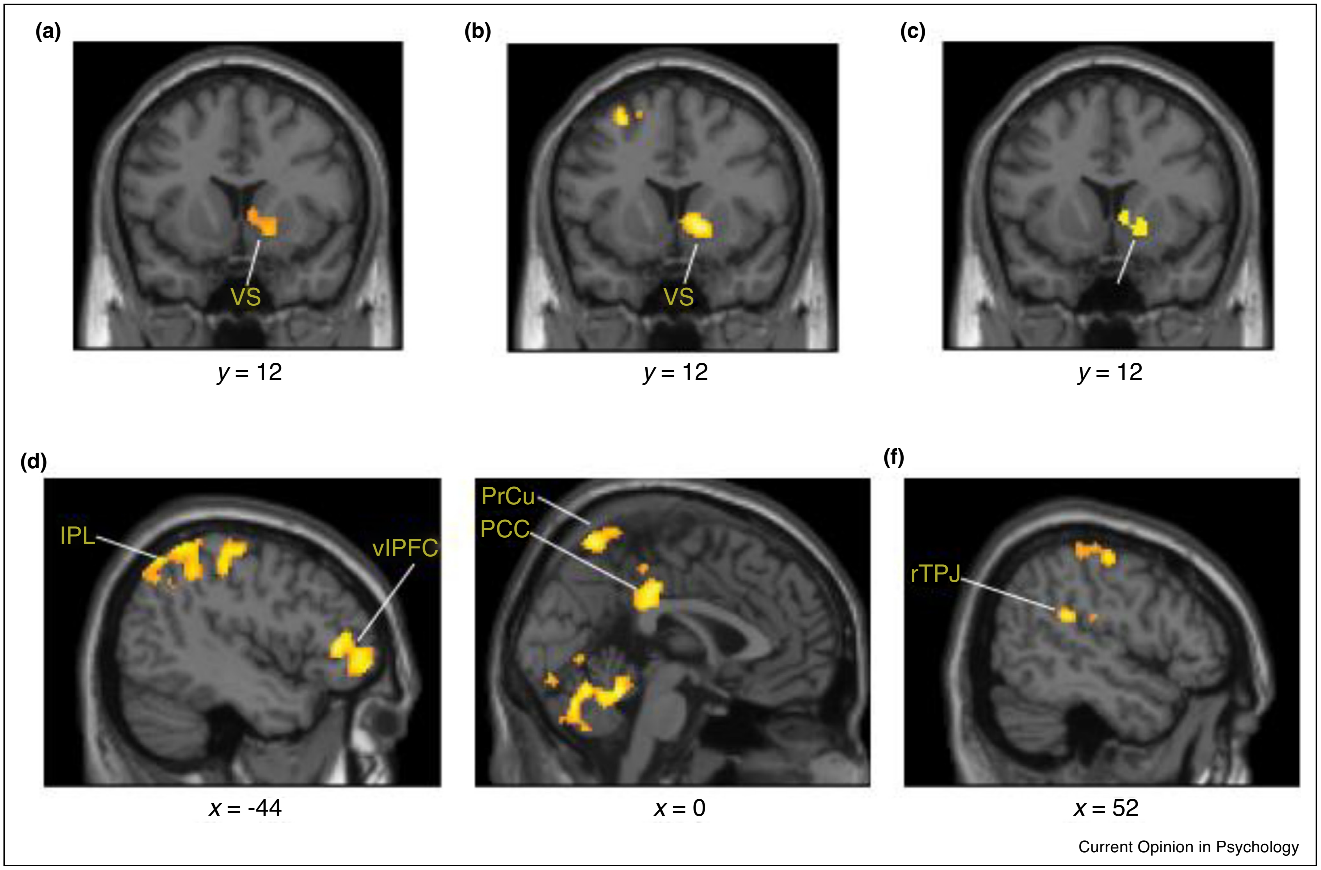
A key advantage of social living is that we learn from the mistakes and insights of others—a process known as observational learning [48]. Computational approaches can identify whether direct and observational learning rely on overlapping or distinct neural processes. During fear conditioning, a passive form of learning, similar neural computations support both processes [49]. In contrast, during instrumental learning, an active form of learning, different computations seem to support learning from experience and observation [50]. During both observational and direct instrumental learning, frontoparietal regions track whether an outcome is surprising; this response may reflect an abstract understanding of reward contingencies. During direct instrumental learning, ventral striatum further reflects whether an outcome is more rewarding than expected, suggesting the role of a second memory process [12,51,52].

Even without seeing others' outcomes, merely observing others' decisions can influence one's own choices [53–57]. Computational models allow researchers to test whether people use this social information optimally in light of their own uncertainty [5•] and to dissociate component processes underlying social influence [57]. Such studies thus reveal how social observation and direct experience are tracked and integrated in the brain.

Morality

People often must choose how to allocate gain or harm between oneself and others, and computational investigations connect these moral tradeoffs to the broader study

Figure 1



Neural correlates of prediction errors related to reward-based reinforcement and impression formation during social interaction, as revealed through computational modeling. Participants played an economic game in which partners varied in reward value (amount of money they shared) and generosity (proportion of available money they shared). Activity in ventral striatum (VS) correlated with **(a)** reward prediction errors and **(b)** generosity prediction errors; overlap shown in **(c)**. Notably, generosity prediction errors also correlated with activity in a set of regions previously associated with impression updating, including **(d)** ventrolateral prefrontal cortex (vlPFC) and inferior parietal lobule (IPL), **(e)** posterior cingulate cortex (PCC) and precuneus (PrCu), and **(f)** right temporoparietal junction (rTPJ). Reprinted from reference [7••].

of learning and choice [58]. Computational models can identify latent variables underlying these choices—such as the extent to which one values another's well-being or feels uncertain about another's preferences—and link these latent variables to brain activity [59,60,61••].

Computational studies have additionally brought new attention to the learning processes that give rise to moral judgments [62–64] and prosocial behavior [28,65,66]. For example, past work suggests that people reciprocate with individuals perceived to be generous [67,68]. Yet, reinforcement learning models suggest that people also like individuals who provide them with large material rewards [7••]. Indeed, people reciprocate more with wealthier partners who provide large material rewards, and this tendency correlates with the extent which people engage in reward-based learning [65]. This work thus reveals how learning dynamics give rise to morality.

Conclusion

The computational approach to social neuroscience offers important tools for elucidating the neural and cognitive processes that drive social cognition and behavior. This approach reflects a natural progression from documenting neural activations to probing their dynamic functions, and it is being applied to an expanding array of social processes—a harbinger of exciting innovations to come in the study of the social brain.

Conflict of interest statement

Nothing declared.

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