Neural Circuitry of Reward Prediction Error

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Abstract

Dopamine neurons facilitate learning by calculating reward prediction error, or the difference between expected and actual reward. Despite two decades of research, it remains unclear how dopamine neurons make this calculation. Here we review studies that tackle this problem from a diverse set of approaches, from anatomy to electrophysiology to computational modeling and behavior. Several patterns emerge from this synthesis: that dopamine neurons themselves calculate reward prediction error, rather than inherit it passively from upstream regions; that they combine multiple separate and redundant inputs, which are themselves interconnected in a dense recurrent network; and that despite the complexity of inputs, the output from dopamine neurons is remarkably homogeneous and robust. The more we study this simple arithmetic computation, the knottier it appears to be, suggesting a daunting (but stimulating) path ahead for neuroscience more generally.

Contents

INTRODUCTION 374
RPE CODING BY DOPAMINE NEURONS 374
Dopamine and RPE: An Introduction 374
Arithmetic of Dopamine Prediction Errors 375
Functions of Dopamine Prediction Error Signals 377
Complexities in the Dopamine Signal 378
COMPUTATION OF DOPAMINE PREDICTION ERRORS 380
Models of the Prediction Error Computation 380
Anatomy of Dopamine Inputs 381
Electrophysiology of Inputs 384
Local Connections in Ventral Tegmental Area 385
Functional Studies: Causality of Inputs 386
PROGRESS AND FUTURE DIRECTIONS 387

INTRODUCTION

The brain is a prediction-making machine. Is that bobbing circle in the distance a human face? Whose face is it? How quickly will she arrive? For every piece of sensory information, our brains use stored patterns to generate a series of predictions. For each of these predictions, an outcome is ultimately experienced. The difference between prediction and outcome is the prediction error, which is thought to be a fundamental way that the brain learns from experience. If the error is small, there is no need to learn. If the error is large, however, the prediction must be updated. In this way, the brain ensures more optimal predictions in the future.

Predictive coding—the idea that the brain generates hypotheses, which are then tested against sensory evidence—has been discussed in a multitude of contexts, from visual processing to motor learning, cerebellum to cortex, simple organisms such as electric fish to complex human diseases such as schizophrenia (Friston 2012, Rao & Ballard 1999). Here we discuss one type of prediction error—reward prediction error (RPE)—and one circuit that encodes it: the dopamine circuit. Synthesizing classic and recent findings, we develop a model for how dopamine neurons calculate RPE and how this signal is broadcast to the rest of the brain.

RPE CODING BY DOPAMINE NEURONS

Dopamine and RPE: An Introduction

The idea that RPEs help guide learning emerged first in psychology, with seminal work by Bush, Mosteller, Kamin, Rescorla, and Wagner, among others (Bush & Mosteller 1951, Kamin 1969, Rescorla & Wagner 1972). Exploiting intricate behavioral tasks, these pioneers discovered that simple repetition was not always enough for animals to form a durable association between stimuli and outcome. To ensure learning, surprise (i.e., an outcome different than expected) was critical. Later, this concept was appropriated by computer scientists, who created prediction-error algorithms to optimize how a computerized agent explores an unknown environment (Sutton & Barto 1998). Indeed, prediction errors continue to play a role in even the most advanced computational algorithms, such as the one that recently mastered the game of Go (Silver et al. 2016).

In the mid-1990s, these models of learning gained a neurobiological flare when Schultz and colleagues demonstrated the remarkable similarity between dopamine neuron firing rates and the RPE signal (Mirenowicz & Schultz 1994, Montague et al. 1996, Schultz et al. 1997, Waelti et al. 2001). When monkeys receive unexpected reward, dopamine neurons fire a burst of action potentials. If the monkeys learn to expect reward, that same reward no longer triggers a dopamine response. Finally, if an expected reward is omitted, dopamine neurons pause their firing at the exact moment reward is expected (Hollerman et al. 1998). Together, these results suggest that dopamine neurons signal the difference between the reward an animal expects to receive and the reward it actually receives. When reward is greater than expected, dopamine neurons fire; when reward is the same as expected, there is no response; and when reward is less than expected, activity is suppressed.

Over the past 20 years, numerous electrophysiological and electrochemical recordings have confirmed and elaborated these results, investigating the properties of dopamine prediction errors and how these signals might facilitate learning in the brain (Glimcher 2011; Schultz 2013, 2016a). Activities consistent with RPEs have been demonstrated in monkeys (Bayer & Glimcher 2005, Enomoto et al. 2011), rats (Day et al. 2007, Flagel et al. 2011, Hart et al. 2014, Oleson et al. 2012, Roesch et al. 2007, Stuber et al. 2008), and humans (D'Ardenne et al. 2008) and appear to faithfully encode various features that determine reward value: probability (Fiorillo et al. 2003), magnitude (Bayer & Glimcher 2005, Bayer et al. 2007, Tobler et al. 2005), timing (Fiorillo et al. 2008, Hollerman et al. 1998, Kobayashi & Schultz 2008), and even subjective preference (Lak et al. 2014).

One limitation in the above electrophysiological studies is that the identification of dopamine neurons was based on indirect physiological properties such as wide spike waveforms (Grace & Bunney 1983, Schultz 1986, Ungless & Grace 2012). These criteria are not always reliable (Lammel et al. 2008, Margolis et al. 2006). To circumvent these problems, Cohen et al. (2012) used optogenetics (Boyden et al. 2005, Lima et al. 2009) to definitively identify dopaminergic neurons while recording in the ventral tegmental area (VTA). The authors tagged dopamine neurons with the light-sensitive cation channel channelrhodopsin-2 (ChR2). Then, at the beginning and end of each recording session, they delivered pulses of blue light through a fiber optic directly into the region of VTA being recorded. Dopamine neurons identified using this approach showed RPE-related activities, confirming previous studies (Cohen et al. 2012, Tian & Uchida 2015) (**Figure 1*a*,*b***). More recently, Stauffer et al. (2016) applied this technique in a nonhuman primate, opening the possibility that researchers could perform rigorous identifications in nonhuman primates.

Arithmetic of Dopamine Prediction Errors

How do dopamine neurons calculate RPE? Reinforcement learning models long assumed that dopamine neurons perform subtraction (i.e., RPE = actual reward − expected reward). However, this arithmetic was never explicitly tested against alternative possibilities.

To explore the nature of the computation, it is helpful to think of dopamine neurons as if they were sensory neurons—but instead of encoding the decibels of a sound, for example, they encode the extent of prediction error. Sensory neurons transform external information into an internal variable: firing rate. If a neuron is tuned to a particular stimulus (e.g., sound), then the more intense the stimulus, the more that neuron will fire. Often a neuron responds minimally to low intensities, increases its response with a certain slope, and then saturates at an asymptotic level, resembling a sigmoid. This input-output function, however, is not fixed: The threshold, slope, and saturation level are all modulated by the nature of sensory inputs and the context in which they are presented. These changes in response functions are examples of neuronal arithmetic and are thought to be essential for the brain to process behaviorally relevant sensory information (Silver 2010, Uchida et al. 2013). In particular, the fields of vision (Atallah et al. 2012, Lee et al. 2012, Williford &

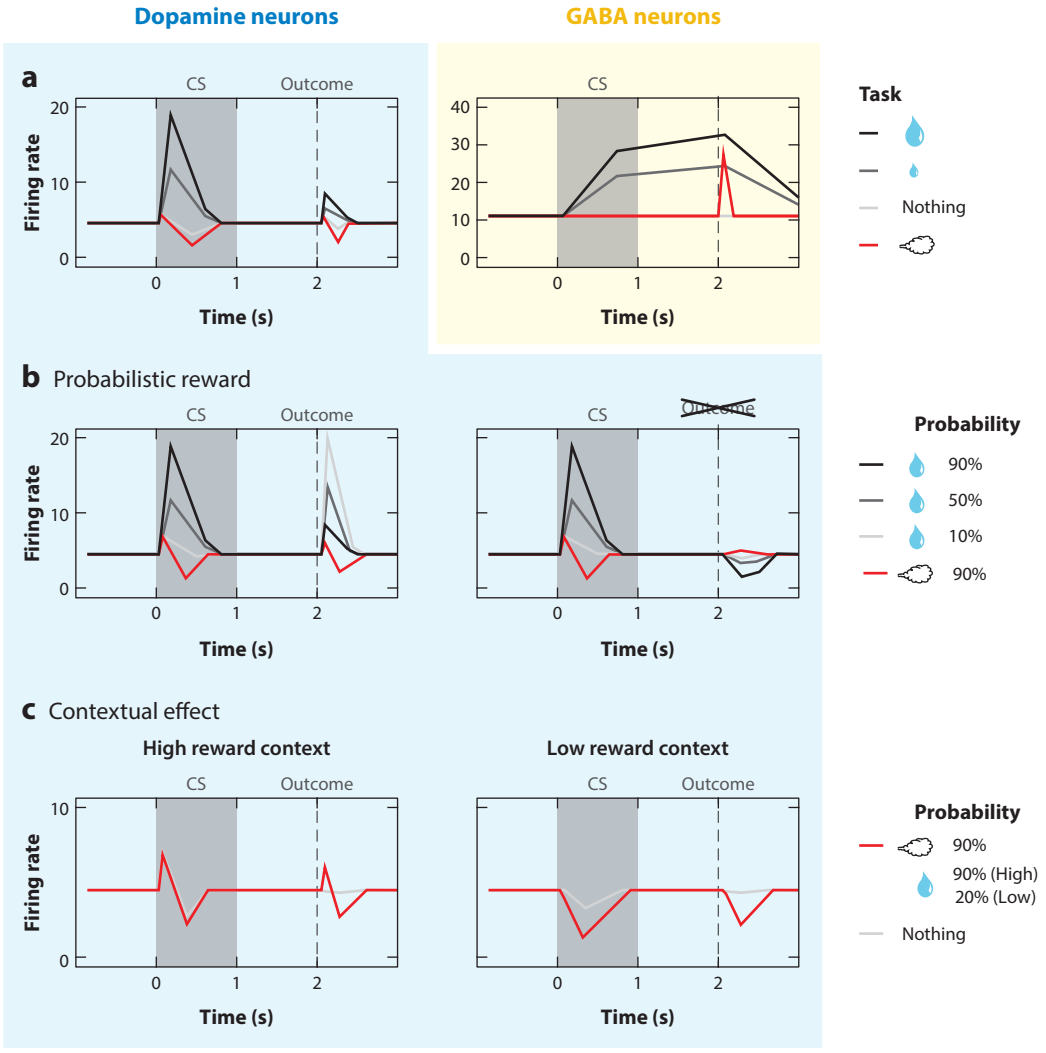


Figure 1

Firing patterns of identified dopamine and GABA neurons in VTA. (*a*) VTA neurons were recorded while mice performed an odor-outcome association task in which different odors predicted different outcomes (see legend on *right*). Odors were presented for 1 s (*gray shading*), and outcomes were presented after a 1-s delay. Neuron types were identified based on their optogenetic responses. Dopamine neurons (*left*) showed phasic excitations to reward-predictive cues and reward. GABA neurons (*right*) showed sustained activation during the delay. Data from Cohen et al. (2012). (*b*) Reward expectation modulates dopamine neuron firing. The plot on the left shows when outcome was presented, and the right-hand plot shows when outcome was omitted. Different odors predicted reward with different probabilities. Higher reward probability increased cue responses but suppressed reward responses. Data from Tian & Uchida (2015). Also see Fiorillo et al. (2003) and Matsumoto & Hikosaka (2009a,b). (*c*) Reward context-dependent modulation of dopamine responses to air puff–predictive cues and air puff. The task conditions during recording differed only in the probability of reward. Dopamine neurons showed both excitation and inhibition in high-reward contexts (*left*) but only inhibition in low-reward contexts (*right*). The response in reward trials is not shown. Data from Matsumoto et al. (2016). Abbreviations: CS, conditioned stimulus; VTA, ventral tegmental area.

Maunsell 2006, Wilson et al. 2012) and olfaction (Kato et al. 2013, Miyamichi et al. 2013, Olsen et al. 2010, Papadopoulou et al. 2011) abound with examples of neuronal arithmetic, with a rich modeling (Ayaz & Chance 2009, Holt & Koch 1997, Murphy & Miller 2003) and experimental (Cardin et al. 2008, Chance et al. 2002, Olsen et al. 2010, Shu et al. 2003) literature exploring the biophysical mechanisms that might underlie it. Until recently, this type of analysis was lacking in the dopamine field.

Although many models of reinforcement learning assumed subtraction, division is equally possible and in fact much more commonly found in other systems in the brain (Silver 2010). To find out which computation dopamine neurons use, Eshel et al. (2015) recorded from optogenetically identified dopamine neurons in lateral VTA as mice performed a simple classical conditioning task. Mice received various sizes of water reward: Sometimes these rewards were delivered unexpectedly, in the absence of any cue, and sometimes they were preceded by an odor cue. By using several different reward sizes, the authors inferred the full dose-response function for dopamine neurons (i.e., the number of spikes that dopamine neurons fired for various rewards) (**Figure 2*a***). They then compared this response function when reward was expected (because of a cue) or unexpected (**Figure 2*b***). The authors found that expectation reduces the phasic reward responses of dopamine neurons in a purely subtractive fashion (**Figure 2*c***). No matter the reward size, a given level of expectation caused a consistent decrease in dopamine responses. This is an unusual computation in the brain but one that is consistent with classic reinforcement learning models.

These analyses were done by averaging over all recorded dopamine neurons. As a population, then, dopamine neurons use simple subtraction. How do individual neurons make this computation? In a subsequent paper, Eshel et al. (2016) determined the full prediction error functions for each individual dopamine neuron in lateral VTA and assessed how these functions related to each other. They found remarkable homogeneity among neurons. Each dopamine neuron appeared to use the same function, just scaled up or down (**Figure 2*d***). Thus, dopamine neurons provide an ideal broadcast signal: similar enough from neuron to neuron that downstream targets could decode the same information regardless of the subset of dopamine neurons that they contact. Such robust encoding had long been inferred (Fiorillo et al. 2013, Glimcher 2011, Schultz 2013), but the quantitative relationship between individual neurons had never been demonstrated.

Functions of Dopamine Prediction Error Signals

Researchers have long thought dopamine to be a key regulator of reward-based learning (Wise & Rompre 1989). The above findings indicate that dopamine can drive learning through signaling prediction error. Recent experimental findings using newer techniques have reinforced this idea, although they by no means exclude other functions of dopamine (Wise 2004). With optogenetics, it became possible to manipulate dopamine neurons with the temporal and genetic precision required to probe their causal effect on learning. Using this technique, researchers have shown that activation or inhibition of dopamine neurons is sufficient to reinforce a behavior positively (Tsai et al. 2009, Witten et al. 2011) or negatively (Danjo et al. 2014, Tan et al. 2012, van Zessen et al. 2012), respectively. Importantly, using the so-called blocking paradigm, Steinberg et al. (2013) demonstrated that phasic increases in dopamine firing were sufficient for prediction error–induced learning. Stimulating dopamine neurons at the time of an expected reward caused rats to learn an association with an otherwise blocked cue, presumably through positive prediction errors. Conversely, Chang et al. (2016) used the paradigm of Pavlovian overexpectation to show that phasic decreases in dopamine responses were also sufficient to produce learning, this time through negative prediction errors. Together, these results demonstrate that dopamine prediction errors regulate learning in both positive and negative directions.

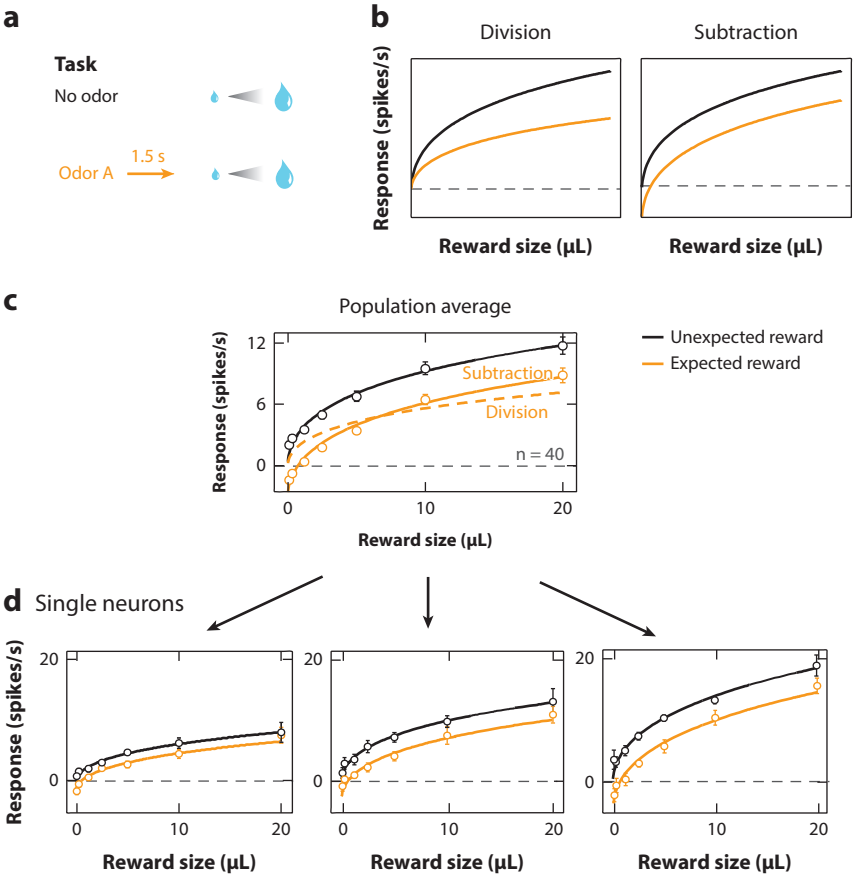


Figure 2

Subtractive computation in dopamine neurons. (*a*) In one task condition (no odor, *black*), different amounts of reward were presented without any predictive cue. In another condition (odor A, *orange*), the timing of reward was predicted by an odor. (*b*) Prediction. Division should change the slope of the curve, whereas subtraction should cause a downward shift. (*c*) Average response of 40 optogenetically identified dopamine neurons. Prediction caused a subtractive shift. Data from Eshel et al. (2015). (*d*) Three example neurons. Although individual neurons exhibited diversity with respect to response magnitudes, their response functions were scaled versions of one another. Data from Eshel et al. (2016).

Complexities in the Dopamine Signal

So far we have seen evidence favoring a very simple story: Dopamine neurons calculate prediction error by subtracting expected from actual reward and then broadcast this signal accurately and consistently to target regions in the brain, promoting learning from trial and error. This simple story, however, belies very important complexities in the nature of this signal.

The findings above on the homogeneity of dopamine prediction error functions fit with a classic literature showing that dopamine neurons have stereotyped electrophysiological properties (Grace & Bunney 1983), couple with each other electrically (Vandecasteele et al. 2005), and coordinate their in vivo firing rates (Joshua et al. 2009, Kim et al. 2012, Morris et al. 2004, Schultz 1998). However, it is now clear that dopamine neurons are not all the same (Bromberg-Martin et al. 2010,

Volman et al. 2013). A host of recent studies have shown diversity in every aspect of dopamine neurons: from their physiology (Margolis et al. 2006, Neuhoff et al. 2002) to their connectivity (Lammel et al. 2008, 2012; Watabe-Uchida et al. 2012) and even their genetic profiles (Blaess et al. 2011, Haber et al. 1995).

Importantly for this review, some dopamine neurons do not faithfully calculate prediction error in the first place. Instead, they increase their firing to both rewarding and aversive events (Fiorillo et al. 2013, Horvitz 2000, Joshua et al. 2008, Lerner et al. 2015, Matsumoto & Hikosaka 2009b). Rather than encoding the difference between actual and predicted outcome, these neurons might encode motivational salience or the absolute value of this difference (Matsumoto & Hikosaka 2009b). Mostly found in more lateral regions of the midbrain, particularly the substantia nigra pars compacta (SNc) [presumably projecting to the dorsal striatum (DS)], these neurons may be important in marking behaviorally important stimuli rather than in updating value assignments (Matsumoto & Hikosaka 2009b) (but see Fiorillo et al. 2013).

Although the nature of these noncanonical dopamine signals remains to be further characterized, a preponderance of evidence suggests that dopamine in the nucleus accumbens (Acb) encodes prediction error signals relatively faithfully in simple tasks (Flagel et al. 2011, Hart et al. 2014, Stuber et al. 2008, Wenzel et al. 2015). Roitman et al. (2008) reasoned that release of dopamine in Acb in response to aversive stimuli may be due to confounding factors such as the difference in sensory modality or intensity. To control for these differences, they used sucrose and quinine solutions for appetitive and aversive stimuli, respectively. They found that these stimuli caused opposite responses: Sucrose increased and quinine decreased dopamine release in the Acb, suggesting that at least the majority of dopamine neurons projecting to the Acb are inhibited by aversive stimuli (Roitman et al. 2008). Another study showed that Acb dopamine could be elevated when an animal avoided an aversive event successfully, suggesting that some of the excitation to aversive stimuli could be regarded as a safety signal (Oleson et al. 2012, Wenzel et al. 2015).

Another important factor to be considered is that dopamine neurons' responses may depend on reward context (Kobayashi & Schultz 2014). Previous studies that recorded from optogenetically identified dopamine neurons typically found biphasic responses (short-latency, transient excitation followed by inhibition) to air puff or air puff–predictive cues (Cohen et al. 2012, Tian & Uchida 2015) (**Figure 1*a*,*b***). A recent study, however, found that most dopamine neurons in lateral VTA show pure inhibition to cues predicting aversive air puffs in a certain task condition (Matsumoto et al. 2016). The difference is due to reward context: The short-latency, transient excitation appears in high reward contexts but disappears in low reward contexts (**Figure 1*c***). Therefore, some of the excitatory responses to aversive events can be due to the effect of high-reward contexts, which are used commonly in recording experiments (Cohen et al. 2012, Tian & Uchida 2015). Schultz (2016b) recently posited that there are two components of the phasic dopamine signal. An initial stage (the first approximately 200 ms) is unselective, detecting physical salience, rather than prediction error. Matsumoto et al. (2016), discussed above, showed that this initial response is more vulnerable to context-dependent modulations. Later on, from 200–400 ms after stimulus onset, dopamine neurons show a more fine-grained prediction-error response (Schultz 2016b), which could be obscured by the initial response in certain conditions such as in high-reward contexts (Fiorillo 2013, Matsumoto et al. 2016).

Besides prediction errors, some dopamine neurons also appear to encode movement-related information (Howe & Dombeck 2016, Jin & Costa 2010, Kim et al. 2015, Parker et al. 2016). Howe & Dombeck (2016), for example, found that dopamine axons projecting to the DS elevate their activity transiently at about the onset of locomotor movements (also see Jin & Costa 2010). Other studies found that dopamine activity can be modulated by the direction of movement (Kim et al. 2015, Parker et al. 2016). Furthermore, more sustained or ramping dopamine signals have

been found when the animal is engaged in certain task conditions (Hamid et al. 2016, Howe et al. 2013, Takahashi et al. 2011) (but see Gershman 2014).

The physiology of the dopamine signal appears more complex the more it is studied. As discussed above, there is certainly diversity of responses, pointing to the importance of characterizing dopamine responses with the firm knowledge of their neurochemical identity as well as their projection targets. At the same time, recent experiments have provided stronger evidence that RPE constitutes a core component of the dopamine signal. To understand the circuit mechanism, it is, therefore, helpful to return to the simplest version of RPE and design experiments to understand how this simple arithmetic can be instantiated by a neural network. What are the inputs and how are they combined?

COMPUTATION OF DOPAMINE PREDICTION ERRORS

Models of the Prediction Error Computation

As discussed above, the activity of dopamine neurons can be approximated by simple equations (Eshel et al. 2015, Schultz et al. 1997). Multiple theories have proposed how RPE could be computed in the brain (Brown et al. 1999, Hazy et al. 2010, Houk et al. 1995, Joel et al. 2002, Kawato & Samejima 2007, Schultz 1998, Schultz et al. 1997, Stuber et al. 2008, Tan & Bullock 2008, Vitay & Hamker 2014). Although there are numerous differences between these models, most boil down to three components: regions that encode expectation; regions that encode actual reward; and the subtraction of these inputs at a common downstream target, usually dopamine neurons themselves. This system explains nicely how dopamine neurons respond to unexpected or expected reward. However, important mysteries remain, including how dopamine neurons become excited by reward-predicting cues or inhibited by omission of expected reward. How is reward information transferred from the reward itself to earlier stimuli? And how does the system learn the precise timing of reward?

To answer these questions, the temporal difference (TD) learning model posits that the cue and omission responses both emerge from the same inputs (Houk et al. 1995, Kawato & Samejima 2007, Morita et al. 2013, Schultz et al. 1997, Sutton & Barto 1998) (**Figure 3*a***; also see the Supplemental Code titled MATLAB Code for the Temporal Difference Error Model). In the simplest version, there are two sustained expectation signals, both of which rise at the cue predicting reward and fall at the time of reward itself. One of these signals [$V(t)$] is inhibitory, whereas the other [$V(t+1)$] is excitatory. Importantly, the inhibitory signal is slightly temporally shifted, so that it begins and ends later than the excitatory signal. By summing these signals, dopamine neurons would show phasic excitation at reward-predicting cues and inhibition at reward omission (**Figure 3*a***). In other words, RPE is generated by taking the derivative of reward prediction.

TD models are successful in explaining many aspects of dopamine RPEs and provide a link between the dopamine reward circuit and machine learning mechanisms. However, this does not prove that RPEs are calculated exactly as the equation predicts. It remains unclear whether the precise time-shift between $V(t)$ and $V(t+1)$, required for TD error calculations, is realistic or what neural substrates could underlie such signals. Thus, another group of models posits that multiple inputs separately represent reward prediction at the conditioned stimulus (CS) and at the unconditioned stimulus (US) (Brown et al. 1999, Contreras-Vidal & Schultz 1999, Hazy et al. 2010, O'Reilly et al. 2007, Tan & Bullock 2008, Vitay & Hamker 2014) (**Figure 3*b*,*c***). One set of inputs excites dopamine neurons at the reward-predicting cue and another inhibits reward responses when reward is predicted. The latter system may also produce the dopamine dip when reward is omitted, or this could be accomplished by a third input. Using separate systems is

Supplemental Material

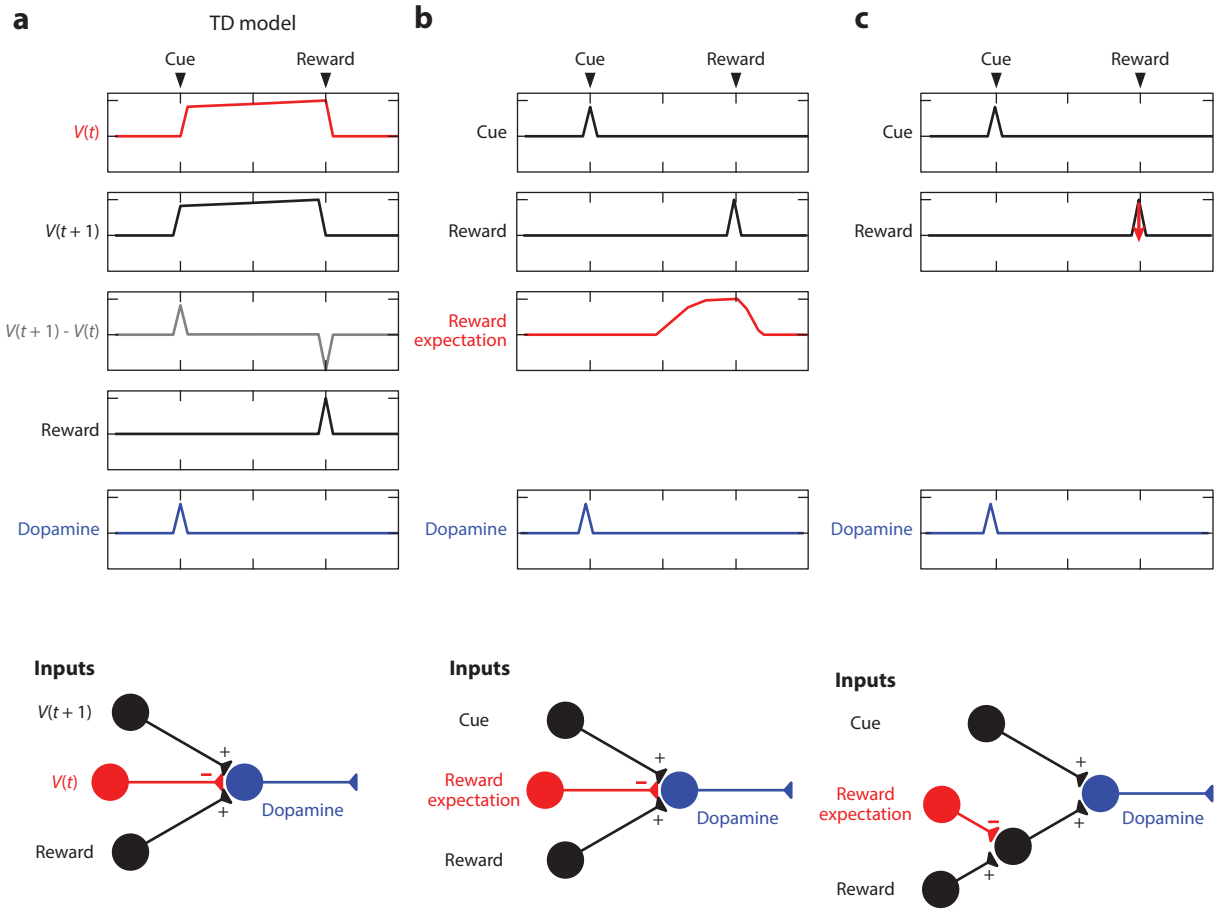


Figure 3

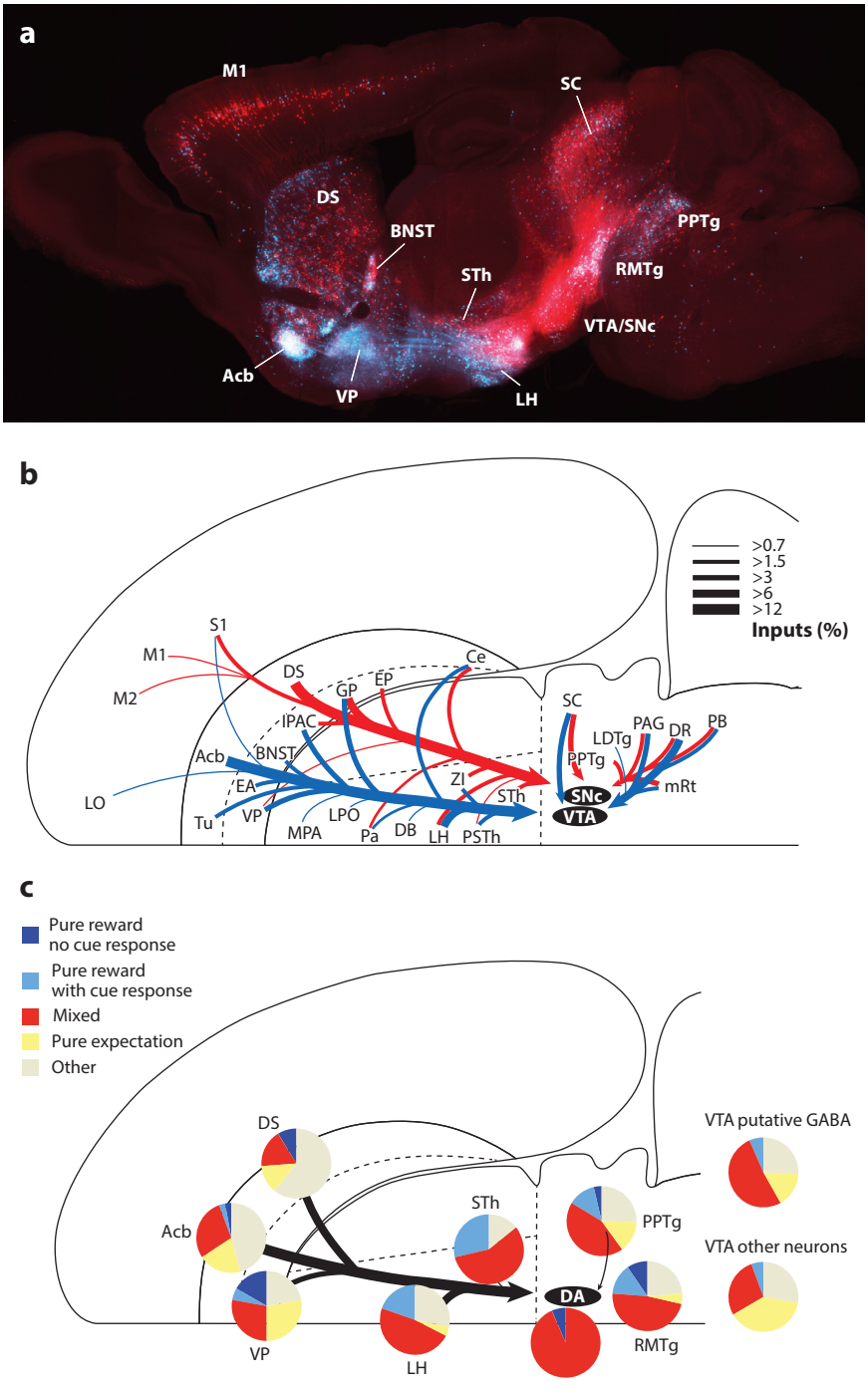
Models of RPE computations. (*a*) TD error model as implemented in Schultz et al. (1997). The computation of TD errors, $\delta = r + V(t+1) - V(t)$, can be seen as combining three inputs, one for each term. The traces show how each term changes as a function of time in a classical conditioning paradigm. The gray trace, $V(t+1) - V(t)$, can be seen as the temporal derivative of the value function, $V(t)$. The dopamine response during reward omission can be approximated by $V(t+1) - V(t)$ (*gray*). (*b*,*c*) Alternative models assuming that reward-predictive cues and reward elicit phasic excitation. Reward expectation modulates dopamine reward responses either at the dopamine neuron itself (*b*) or upstream (*c*). Abbreviations: RPE, reward prediction error; TD, temporal difference.

advantageous in the sense that it provides flexibility to build complex features, such as independent learning rates or variable timing.

Finally, several authors have suggested that prediction error is calculated not by dopamine neurons at all, but rather in upstream areas such as the rostromedial tegmental nucleus (RMTg) (Jhou et al. 2009) or lateral habenula (lHb) (Hong et al. 2011; Matsumoto & Hikosaka 2007, 2009a). The information is then relayed to dopamine neurons. In this view, the dopamine neurons are passive conveyers of information, rather than active comparators of actual and predicted reward.

Anatomy of Dopamine Inputs

To distinguish between these models and understand how dopamine RPE signals are generated, we start with anatomy. Which brain areas actually project to dopamine neurons? Using retrograde



tracers, Zahm and colleagues (Geisler & Zahm 2005, Geisler et al. 2007) systematically examined projections to VTA and found extensive sources of inputs, particularly around the medial forebrain bundle. Importantly, the authors proposed that brain areas that project directly to VTA tend to also project indirectly to VTA. For example, there is a loop from prefrontal cortex to Acb to ventral pallidum (VP) to lateral hypothalamus (LH) to VTA, suggesting an interconnected anatomical network for the regulation of dopamine neurons.

Although informative, conventional retrograde tracers cannot distinguish cell types of the target areas. Because VTA consists of dopamine neurons, GABA neurons, and glutamate neurons, some of the areas that project to VTA may not in fact project to dopamine neurons. To overcome this barrier and label monosynaptic inputs to dopamine neurons specifically, Watabe-Uchida et al. (2012) applied a modified rabies virus system (Wickersham et al. 2007). Using this system, the authors mapped inputs to dopamine neurons comprehensively and found many brain areas that project directly to dopamine neurons (**Figure 4*a*,*b***). Comparing inputs to dopamine neurons in VTA and SNc, the authors proposed that lateral orbitofrontal cortex (OFC) and LH are the major excitatory inputs to VTA, whereas sensorimotor cortex and subthalamic nucleus are the major excitatory inputs to SNc. On the other hand, the ventral and dorsal nuclei in the basal ganglia (the Acb and VP, versus the DS, globus pallidus, entopeduncular nucleus, and substantia nigra reticulata) provide the major inhibitory inputs to dopamine neurons in VTA and SNc, respectively.

The above study mapped inputs to dopamine neurons in VTA and SNc regardless of where those dopamine neurons project. However, it is well known that dopamine neurons within a given region may project to a diverse array of targets. Thus, the previous study might have observed so many monosynaptic inputs because the dopamine neurons were themselves diverse. Recent studies tackled this problem by mapping monosynaptic inputs to subpopulations of dopamine neurons that project to specific brain areas (Beier et al. 2015, Lerner et al. 2015, Menegas et al. 2015). These studies found that even when the projection targets of dopamine neurons were specified, there were still monosynaptic inputs from numerous brain areas. Menegas et al. (2015) found that, for seven of the eight examined subpopulations of dopamine neurons, monosynaptic inputs were largely overlapping. Unexpectedly, however, dopamine neurons that projected to the tail of the striatum (TS, the most posterior part of the striatum) received a different set of inputs, suggesting that the function of TS-projecting dopamine neurons might be different from most dopamine

Figure 4

Monosynaptic input to dopamine neurons. (*a*) Monosynaptic inputs to VTA and SNc dopamine neurons (*blue* and *red*, respectively). Inputs were labeled through transsynaptic retrograde tracing using rabies virus. Data from Watabe-Uchida et al. (2012). (*b*) Schematic summary of panel *a*. The thickness of each line indicates the extent of inputs from each area (percentage of total inputs). (*c*) Firing patterns of monosynaptic inputs in a classical conditioning paradigm. Monosynaptic inputs to dopamine neurons were labeled by channelrhodopsin-2 using rabies virus. Optogenetics were used to identify these inputs in seven brain areas while mice performed a task. Data from Tian et al. (2016). Abbreviations: Acb, nucleus accumbens; BNST, bed nucleus of stria terminalis; Ce, central amygdala; DA, dopamine; DB, diagonal band of Broca; DR, dorsal raphe; DS, dorsal striatum; EA, extended amygdala; EP, entopeduncular nucleus (internal segment of the globus pallidus); GP, globus pallidus (external segment of the globus pallidus); IPAC, interstitial nucleus of the posterior limb of the anterior commissure; LDTg, laterodorsal tegmental nucleus; LH, lateral hypothalamus; LO, lateral orbitofrontal cortex; LPO, lateral preoptic area; M1, primary motor cortex; M2, secondary motor cortex; MPA, medial preoptic area; mRt, reticular formation; Pa, paraventricular hypothalamic nucleus; PAG, periaqueductal gray; PB, parabrachial nucleus; PPTg, pedunculopontine tegmental nucleus; PSTh, parasubthalamic nucleus; RMTg, rostromedial tegmental nucleus; S1, primary somatosensory cortex; SC, superior colliculus; SNc, substantia nigra pars compacta; STh, subthalamic nucleus; Tu, olfactory tubercle; VP, ventral pallidum; VTA, ventral tegmental area; ZI, zona incerta.

neurons. Assuming that most dopamine neurons encode RPE, the inputs specific to TS-projecting dopamine neurons can be excluded from the list of inputs needed for RPE. The brain areas that remain—those that appear to provide major inputs to RPE-encoding dopamine neurons—are LH, ventral striatum and DS, lateral preoptic area, and VP. With this structural information in hand, the next question is, what information does each area send to dopamine neurons?

Electrophysiology of Inputs

Decades of recordings have provided important hints on candidate brain areas for RPE computations. For example, LH is known to encode reward information such as taste (Ono et al. 1986). Combined with the fact that responses to reward are modulated by internal states such as hunger (Burton et al. 1976), these results suggest that LH may encode subjective values, which could be sent to dopamine neurons directly or indirectly. By contrast, striatal neurons respond to reward-predicting cues, often showing sustained excitation (Hikosaka & Sakamoto 1986, Schultz et al. 1993). Together with the fact that the overwhelming majority of striatal neurons are inhibitory, this response pattern makes the striatum a good candidate for providing the expectation signal. Because the striatum is the main projection target of dopamine neurons, reciprocal connections between the striatum and dopamine neurons would make learning straightforward: The striatum sends predicted value and dopamine neurons return prediction error. Furthermore, direct and multisynaptic pathways from the striatum to dopamine neurons imply several potential mechanisms to produce RPE.

Electrophysiology can be incredibly informative, but there are important pitfalls in the interpretation of these results. First, although recording experiments can find interesting activity in a given brain area, other areas may have the same responses—hence the need for the systematic study of many brain regions, ideally simultaneously. Second, neurons that seem to encode information relevant to the task at hand are often intermingled with neurons that show other types of activity. We seldom know which information is sent to a specific downstream brain target. Third, even if we know the projection target of the neurons, the target brain areas are themselves diverse, and it can be unclear to which specific type of neuron the information is going. In the case of RPEs, the relevant question is which brain areas send information about actual and expected reward to dopamine neurons.

To answer this question directly, Tian et al. (2016) established an awake recording system that combined optogenetics with the modified rabies virus. While mice performed simple classical conditioning tasks, the authors recorded extracellular activity of monosynaptic inputs to dopamine neurons in seven input areas: DS, Acb, VP, LH, subthalamic nucleus, RMTg, and pedunculopontine tegmental nucleus (PPTg) (**Figure 4*c***). Surprisingly, there were input neurons in all seven recorded areas that encoded either actual reward or expectation. In fact, many single-input neurons were modulated by both actual reward and expectation. Thus, information relevant to RPE had already been combined—at least in part—in input neurons. Importantly, however, very few input neurons showed complete reward-prediction-error signals. Thus, dopamine neurons receive a spectrum of information, including pure reward, pure expectation, mixed reward and expectation, partial RPE, and—in rare cases—complete RPE, all from multiple brain areas. This then gets funneled into a pure RPE signal in dopamine neurons. In other words, the brain seems to perform the RPE computation redundantly, in multiple layers.

At first glance, these results are puzzling. The brain appears to solve the problem in a very inefficient way. However, a simple model helps explain the findings. Tian et al. (2016) first created a linear model to reconstruct dopamine activity using the activity of input neurons from all seven areas. They found that a weighted sum of inputs could reconstruct dopamine activity easily. Indeed, even if an entire brain area were removed from the analysis, the remaining inputs could

still reconstruct dopamine RPEs. The same is true even if the weights for each input were totally shuffled: The resulting output still captured aspects of RPE signals. By contrast, if recordings from other neurons in these regions, which were not identified as inputs, were used for the model, the reconstructions became less accurate. These results suggest that the identity of the inputs is important, even if the precise weights between inputs and dopamine neurons are not. Thus, far from being inefficient, the presence of mixed information appears to be a convenient, robust, and ready-to-use format for dopamine neurons to compute RPE.

One open question, then, is whether inputs to dopamine neurons are redundant or specialized. The data presented above suggest the former. Another open question is the importance of excitatory versus inhibitory projections to dopamine neurons. For this, Tian et al. (2016) identified input neurons that could discriminate conditioned stimuli based on probability of reward, and whose responses were fast enough to account for the dopamine CS response. They found that all input neurons that met these criteria were excited by reward cues. Because dopamine neurons are also excited by reward cues, these results suggest that excitatory inputs (particularly in VP, LH, and PPTg) likely cause dopamine phasic responses to CS. In other words, disinhibition (i.e., inhibition of inhibitory inputs) appears to play a very limited role. In fact, this pattern held true for responses to aversive stimuli as well: Most monosynaptic inputs to dopamine neurons were excited by aversive stimuli, implying that the suppression in dopamine neurons must be due to direct inhibition (e.g., from inhibitory neurons in Acb or RMTg), rather than reduced excitation.

The presence of both direct excitation and direct inhibition implies that a combination of inputs must determine the dopamine RPE response, rather than variations in a single type of input. Further evidence for this claim comes from analyzing both the time course and amplitude of dopamine responses. Matsumoto et al. (2016) showed that dopamine excitation to reward-predicting cues occurs faster than inhibition to aversion-predicting cues, implying different inputs for each process. In addition, as mentioned above, Eshel et al. (2016) found that response functions to reward were remarkably uniform from neuron to neuron. It turns out that response functions to aversive stimuli are similarly uniform (Matsumoto et al. 2016). However, responses to reward are not correlated with responses to aversive stimuli (Matsumoto et al. 2016). Furthermore, habenula lesions showed that the dopamine dip during reward omission depends disproportionately on the function of the lHb, whereas the dip to aversive stimuli does not (Tian & Uchida 2015). These findings suggest the presence of multiple separate inputs determining excitation and inhibition in dopamine neurons, raising the possibility that RPE computations consist of multiple mechanisms.

Local Connections in Ventral Tegmental Area

Much of the anatomic and physiological work discussed so far has focused on long-range projections to dopamine neurons. However, dopamine neurons in VTA are surrounded locally by GABA neurons and glutamate neurons, both of which send projections to their dopaminergic neighbors (Sesack & Grace 2010). Because of the vicinity, local connections may have particularly strong effects on dopamine activity.

To dissect the different roles of neurons in VTA, Cohen et al. (2012) recorded from VTA while mice performed classical conditioning tasks. They found three types of activity: Type 1 resembled RPE, with phasic activity to cues and rewards; type 2 resembled reward expectation, with a ramping cue response proportional to expected reward; and type 3 was a mirror image of type 2, with downward-sloping activity dependent on the magnitude of expected reward. Using the optogenetic identification method described above, the authors showed that although identified dopamine neurons were all type 1 (RPE), identified GABA neurons were type 2, signaling reward expectation (**Figure 1*a***).

At this moment, it is not clear whether type 3 neurons are GABAergic or glutamatergic. Of note, RMTg neurons are located together with dopamine neurons at the boundary between VTA and RMTg. Because most neurons in RMTg are GABA neurons and both type 3 and RMTg neurons show inhibition in response to reward cues (Hong et al. 2011, Jhou et al. 2009), they may actually be one and the same. In this case, type 3 neurons would be GABA neurons. However, there are differences in activity between type 3 neurons and RMTg neurons. Whereas many VTA type 3 neurons show sustained inhibition to reward cues and are not modulated by reward itself, most monosynaptic inputs from RMTg are modulated by both cues and rewards (Tian et al. 2016). Further classification—including experiments that tag glutamate neurons with ChR2—will be necessary to clarify the activity patterns of each cell type in VTA.

Functional Studies: Causality of Inputs

Although many models assume that RPE is calculated in dopamine neurons, some have argued that dopamine neurons merely relay already-calculated RPEs. Neurons in the lHb, for example, encode negative RPE (i.e., the mirror image of dopamine RPE). Researchers have therefore proposed that lHb neurons send RPE signals to dopamine neurons via GABAergic neurons in RMTg (Matsumoto & Hikosaka 2007, Stephenson-Jones et al. 2016). If the lHb-RMTg system is the source of dopamine RPE, lesioning lHb should deplete RPE signals in dopamine neurons. Tian & Uchida (2015) tested this theory by lesioning the habenula while recording from optogenetically identified dopamine neurons in VTA. After lesions, dopamine neurons maintained their responses to reward and reward-predicting cues. Thus, consistent with the anatomy study above, the lHb-RMTg cannot be the only source of RPE. However, dopamine neurons did lose their inhibitory responses to reward omission after the habenula lesion, suggesting that these inputs may serve a specific function. Further supporting the specificity of these inputs, dopamine neurons did not lose their responses to all aversive events; they maintained their responses to air puffs. Thus, lHb appears to be important for determining dopamine neurons' inhibition specifically to reward omission. In support of this idea, responses to reward omission were particularly vulnerable to changes in weights or input areas used in the linear combination of inputs discussed above (Tian et al. 2016). Perhaps the information important for reward omission arises in OFC (Feierstein et al. 2006) and then passes through the Acb, entopeduncular nucleus, lHb, and RMTg before reaching dopamine neurons.

Beyond the dip to reward omission, one of the core features of RPE is that the response to reward is diminished when reward is expected. As discussed above, this reduction in reward response occurs through subtraction (Eshel et al. 2015). The obvious next question is, what inputs do dopamine neurons subtract? One possibility is VTA GABA neurons, which were shown to encode reward expectation (Cohen et al. 2012) (**Figure 1*a***). Do dopamine neurons use this signal to calculate RPE? Using optogenetics, Eshel et al. (2015) selectively excited or inhibited VTA GABA neurons while mice performed classical conditioning tasks and determined the effect of this manipulation on putative dopamine responses. They found that stimulating VTA GABA neurons during the delay between the cue and the reward caused a subtraction of dopamine reward responses, mimicking the effect of reward expectation. Conversely, inhibiting VTA GABA neurons during this period increased dopamine responses to expected reward, as if reward were suddenly less expected. Finally, bilaterally stimulating VTA GABA neurons changed the animals' behavior, causing them to reduce their responses to laser-paired cues. This behavior is consistent with GABA stimulation causing an overexuberant prediction signal, which then led to reduced dopamine responses when reward actually came. Together, these results imply that VTA GABA neurons help put the prediction in prediction error. Of course, they may not be the only important

inputs for reward expectation. Importantly, VTA GABA neurons elevate their activity as soon as the reward-predictive cue is presented, whereas dopamine neurons' baseline firing rates are not inhibited significantly (**Figure 1*a***). This suggests that an intricate balance between GABA neuron activity and counteracting excitation, as proposed in TD models (**Figure 3*a***), might underlie this process. Furthermore, Tian et al. (2016) demonstrated that other monosynaptic inputs have similar properties (**Figure 4*c***). Although VTA GABA neurons' proximity and the density of their projections to dopamine neurons may give them an outsized role in RPE calculations, the RPE computation likely depends on inputs from diverse areas.

It remains to be determined where reward expectation is calculated in the first place or what drives the activity of VTA GABA neurons. Previous studies have shown that many neurons in the OFC and Acb change their activity depending on reward expectation. Takahashi and colleagues tested the role of these areas in producing RPE signals in dopamine neurons. First, lesions of lateral and ventral OFC in rats reduced putative dopamine neurons' ability to modulate their responses when the size or timing of reward was changed (Takahashi et al. 2011). Furthermore, Takahashi et al. (2016) found that after lesions of the Acb, putative dopamine neurons lost their ability to modulate their responses when the timing but not the size of reward was altered. These results suggest that OFC or Acb may play a role in the calculation of RPEs. However, these experiments depended on permanent lesions and used a learning paradigm to probe RPEs, making it difficult to dissociate whether altered RPE signaling was a direct effect of the lesion or rather due to an impairment in the animal's ability to learn. Furthermore, it was not possible to examine whether the recorded neurons were indeed dopamine neurons, let alone how the activity of VTA GABA neurons was altered by the lesions. Studying the pathway by which OFC and Acb modulate the activity of dopamine neurons may provide important insights into how neural circuits compute RPEs.

PROGRESS AND FUTURE DIRECTIONS

The idea that dopamine neurons signal RPEs has revolutionized the study of reward processing and decision making in the brain. In particular, the fact that dopamine responses can be well approximated by simple arithmetic equations has prompted many researchers to propose simple models that combine different variables in a single step. However, as more sophisticated anatomic and electrophysiological data have become available, a complicated picture has emerged for the circuit underlying prediction errors. It is now clear, for example, that many brain areas project directly to VTA dopamine neurons (Watabe-Uchida et al. 2012). This is true not just for dopamine neurons as a whole but even for subsets of dopamine neurons defined by their projection targets (Beier et al. 2015, Lerner et al. 2015, Menegas et al. 2015). Moreover, there is striking interconnectivity between these input areas, more often resembling a recurrent neural network than a simple feedforward box-and-arrow diagram (Geisler & Zahm 2005). From the standpoint of electrophysiology, presynaptic neurons or input neurons from all these input areas show a diverse set of responses (Tian et al. 2016). In even the simplest task, it is a rare input neuron that exhibits a pure response to either reward or expectation. Rather, information relevant for RPE computations is mixed and distributed throughout multiple regions. With such complexity, can we ever understand how the brain computes RPE?

Fortunately, despite the complexity, patterns have begun to emerge. The data presented above strongly support the centrality of dopamine neurons in the RPE calculation. Rather than receiving RPE signals passively from upstream regions such as lHb, dopamine neurons appear to be performing computations on their input (Eshel et al. 2015). Although most models assume pure inputs onto dopamine neurons, our work has demonstrated monosynaptic inputs that span from pure (such as reward information from VP, LH, and PPTg) to decidedly mixed (Tian et al. 2016).

Ultimately, dopamine neurons are capable of combining these inputs in such a way to produce a remarkably homogeneous prediction error signal, ideal to broadcast to a wide variety of downstream targets (Eshel et al. 2016).

In terms of the mechanisms behind these computations, phasic increases in dopamine responses appear to be triggered by direct excitation, rather than disinhibition. Likewise, phasic decreases in dopamine responses appear to emerge from direct inhibition, rather than reduced excitation (although reduced excitation in PPTg may enhance prediction-dependent suppression of dopamine reward responses; see Tian et al. 2016).

Furthermore, unlike the simplest TD models, it does not appear that the CS and US responses are due to the same inputs. Instead, dopamine neurons appear to be combining multiple separate inputs, with different signals crucial for cue responses, reward responses, reward omission, and aversion. Indeed, even the dip in dopamine responses when reward is omitted appears to be due to a different input than the reduced but still positive reward response that dopamine neurons exhibit when reward is expected (Eshel et al. 2015, Tian & Uchida 2015). And when it comes to aversive events, the inhibition in dopamine neurons appears to arise from a slower set of inputs than excitation to reward (Matsumoto et al. 2016).

The brain regions involved in this circuit are significantly redundant. Neurons in multiple regions all provide dopamine neurons with information relevant for RPEs. Interestingly, the relative weights of these inputs can change dramatically without affecting the final dopamine response (Tian et al. 2016). However, the inputs are not random—neurons that reside in input regions, but do not themselves project to dopamine neurons, cannot produce the dopamine RPE response easily (Tian et al. 2016). Based on a combination of anatomic and physiological studies, key excitatory inputs include lateral OFC, VP, lateral preoptic area, and LH, whereas inhibitory inputs include VTA GABA neurons, Acb, VP, and lateral preoptic area. Interestingly, VTA GABA neurons receive similar monosynaptic inputs as dopamine neurons (Beier et al. 2015). This sets up the possibility of feedforward inhibition, allowing dopamine neurons to take derivatives, one of the major predictions of TD models.

Although studies have become increasingly specific, with analyses that target specific cell types and projection targets, most have focused on just one type of information flow: from input areas to dopamine neurons. In the future, it will be crucial to analyze flow between input areas as well. For example, although excitatory inputs in multiple areas (VP, LH, and PPTg, to name a few) may trigger phasic responses to rewards and reward-predicting cues in dopamine neurons, VP may be the lynchpin, providing information not just to dopamine neurons but also to these other input regions. By hopping back through each node in the circuit, combining anatomy and physiology at every step, we may be fast approaching the solution to this mysterious and crucial circuit for computing RPEs.

The research discussed above has revealed the unprecedented complexity that underlies a seemingly simple arithmetic computation. This suggests some fundamental limitations that neuroscience faces more generally. First, the ultimate goal of neuroscience is to explain how neural circuits produce complex behavior. To this end, we often develop simple box-and-arrow models in which information flows from area A to B to C. It has also become a common practice to activate a population of neurons artificially and infer functions based on changes in behavior. Although these approaches can be useful, they often ignore far more complex connectivity between these areas and far more diverse activity within each area. The brain is a dynamical system that consists of many diverse and interconnected neurons. It is vital to consider whether these simplified views help our understanding or hide essential features of neural circuits unintentionally.

Second, many of the studies described above relied on monitoring the activity of neurons by recording action potentials. Monitoring spikes together with a neuron's cell type and connectivity

has enhanced our knowledge of neuronal function considerably. Spikes are the main currency with which neurons communicate and are therefore essential to understanding neuronal computations. However, spikes do not necessarily capture all the processes required for RPE computations. Importantly, RPE computations require comparing actual reward against what the animal expects. The latter requires memory about reward in a given context, and memory is likely to be stored in synaptic weights or through intrinsic properties of neurons (Martin et al. 2000, Schultz et al. 1997). Spikes may not represent these memories faithfully because once a neuron fires a spike, the information propagates in neural circuits that affect other neurons as well as itself. At present, our ability to monitor synaptic weights or intrinsic properties of neurons in behaving animals is quite limited. It is possible that the memory that supports RPE computations is stored in a pure fashion. Developing techniques that allow for monitoring synaptic weights, together with other variables (spikes, cell types, and connectivity), will advance our understanding.

Third, the results discussed above reinforce the importance of developing theories about how neural circuits with complex connectivity can perform simple computations robustly and accurately. How is the information stored, and how does it propagate? Are there computational advantages to redundant or distributed computations, versus simple box-and-arrow computations? As is the case in modern artificial neural networks (LeCun et al. 2015), it is often difficult to infer even simple operating principles by looking solely at the component parts. A crucial step is to develop theoretical frameworks that link global, top-down functions with how each component supports these functions. Only with such models can we hope to understand neural circuits, even those as seemingly basic as RPEs.

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Contents

Neurotransmitter Switching in the Developing and Adult Brain
Nicholas C. Spitzer 1

The Microbiome and Host Behavior
Helen E. Vuong, Jessica M. Yano, Thomas C. Fung, and Elaine Y. Hsiao 21

Neuromodulation and Strategic Action Choice in *Drosophila* Aggression
Kenta Asahina 51

Learning in the Rodent Motor Cortex
Andrew J. Peters, Haixin Liu, and Takaki Komiyama 77

Toward a Rational and Mechanistic Account of Mental Effort
Amitai Shenhav, Sebastian Musslick, Falk Lieder, Wouter Kool, Thomas L. Griffiths, Jonathan D. Cohen, and Matthew M. Botvinick 99

Zebrafish Behavior: Opportunities and Challenges
Michael B. Orger and Gonzalo G. de Polavieja 125

Catastrophic Epilepsies of Childhood
MacKenzie A. Howard and Scott C. Baraban 149

The Cognitive Neuroscience of Placebo Effects: Concepts, Predictions, and Physiology
Stephan Geuter, Leonie Koban, and Tor D. Wager 167

Propagation of Tau Aggregates and Neurodegeneration
Michel Goedert, David S. Eisenberg, and R. Anthony Crowther 189

Visual Circuits for Direction Selectivity
Alex S. Mauss, Anna Vlasits, Alexander Borst, and Marla Feller 211

Identifying Cellular and Molecular Mechanisms for Magnetosensation
Benjamin L. Clites and Jonathan T. Pierce 231

Mechanisms of Hippocampal Aging and the Potential for Rejuvenation
Xuelai Fan, Elizabeth G. Wheatley, and Saul A. Villeda 251

Sexual Dimorphism of Parental Care: From Genes to Behavior
Noga Zilkha, Niv Scott, and Tali Kimchi 273

Nerve Growth Factor and Pain Mechanisms
Franziska Denk, David L. Bennett, and Stephen B. McMahon 307

Neuromodulation of Innate Behaviors in *Drosophila*
Susy M. Kim, Chih-Ying Su, and Jing W. Wang 327

The Role of the Lateral Intraparietal Area in (the Study of) Decision Making
Alexander C. Huk, Leor N. Katz, and Jacob L. Yates 349

Neural Circuitry of Reward Prediction Error
Mitsuko Watabe-Uchida, Neir Eshel, and Naoshige Uchida 373

Establishing Wiring Specificity in Visual System Circuits: From the Retina to the Brain
Chi Zhang, Alex L. Kolodkin, Rachel O. Wong, and Rebecca E. James 395

Circuits and Mechanisms for Surround Modulation in Visual Cortex
Alessandra Angelucci, Maryam Bijanzadeh, Lauri Nurminen, Frederick Federer, Sam Merlin, and Paul C. Bressloff 425

What Have We Learned About Movement Disorders from Functional Neurosurgery?
Andres M. Lozano, William D. Hutchison, and Suneil K. Kalia 453

The Role of Variability in Motor Learning
Ashesh K. Dhawale, Maurice A. Smith, and Bence P. Ölveczky 479

Architecture, Function, and Assembly of the Mouse Visual System
Tania A. Seabrook, Timothy J. Burbridge, Michael C. Crair, and Andrew D. Huberman 499

Mood, the Circadian System, and Melanopsin Retinal Ganglion Cells
Lorenzo Lazzerini Ospri, Glen Prusky, and Samer Hattar 539

Inhibitory Plasticity: Balance, Control, and Codependence
Guillaume Hennequin, Everton J. Agnes, and Tim P. Vogels 557

Replay Comes of Age
David J. Foster 581

Mechanisms of Persistent Activity in Cortical Circuits: Possible Neural Substrates for Working Memory
Joel Zylberberg and Ben W. Strowbridge 603

Transcriptomic Perspectives on Neocortical Structure, Development, Evolution, and Disease
Ed S. Lein, T. Grant Belgard, Michael Hawrylycz, and Zoltán Molnár 629