# Dopamine and value

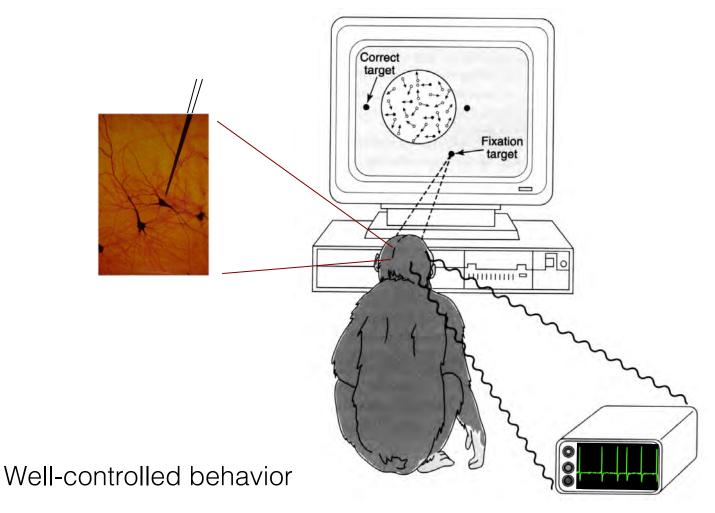
Naoshige Uchida
Center for Brain Science
Dept. of Molecular and Cellular Biology
Harvard University

# Understanding the brain

- Computational theory / goal
- Algorithm
- Implementation

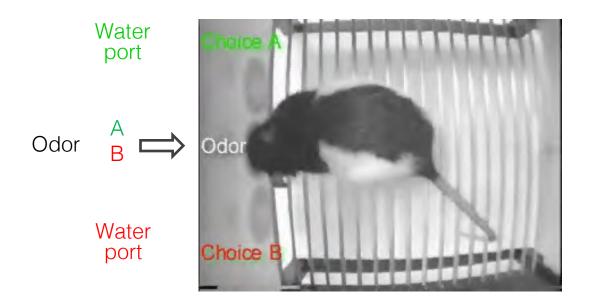
The three levels by David Marr

# Single neuron recording in alert monkey



Recording in awake animal

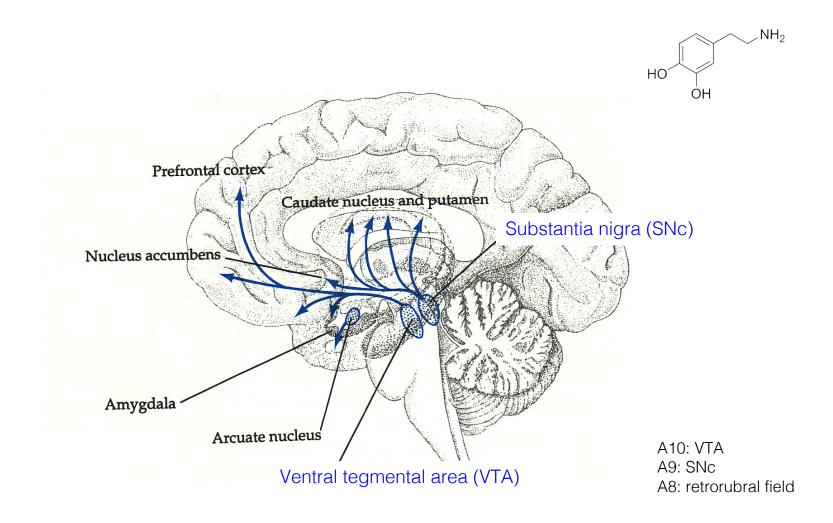
### Our approach: rodent models



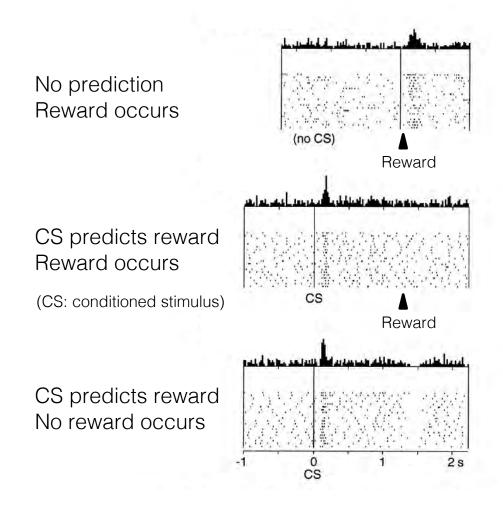
(Uchida and Mainen, 2003)

- Well-controlled behavior
- Electrophysiology
- Molecular/genetic tools

# Dopamine

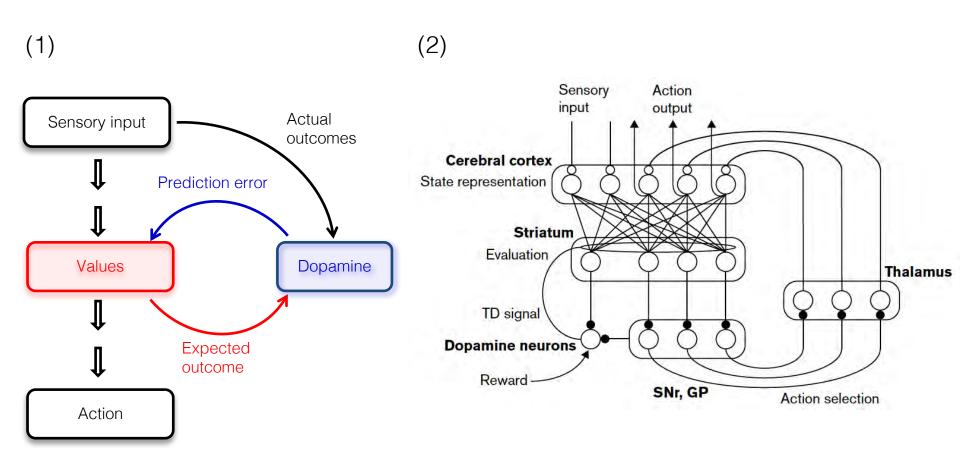


### Firing of putative dopamine neurons



$$\delta(t) = r(t) + \gamma \hat{V}(t+1) - \hat{V}(t)$$

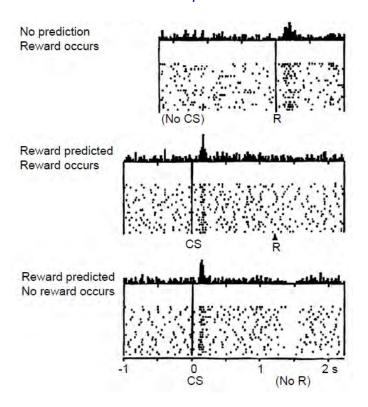
### Reinforcement learning models



### A Neural Substrate of Prediction and Reward

Wolfram Schultz, Peter Dayan, P. Read Montague\*

Neurobiology
 Phasic dopamine

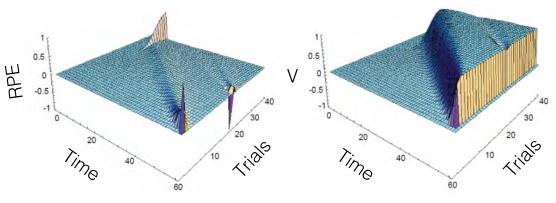


Reinforcement learning
 Temporal difference (TD) learning theory

$$V(t) = E[\gamma^{0}r(t) + \gamma^{1}r(t+1) + \gamma^{2}r(t+2) + \cdots]$$
(1)

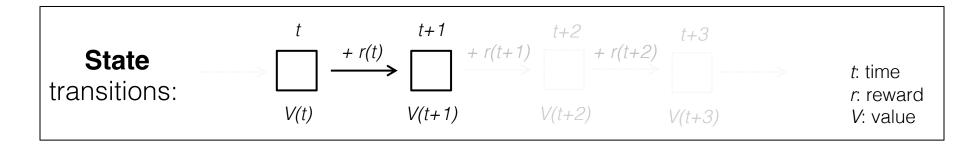
$$V(t) = E[r(t) + \gamma V(t+1)] \qquad (2)$$

$$\delta(t) = r(t) + \gamma \hat{V}(t+1) - \hat{V}(t) \quad (3)$$



Animal learning theory
 Learning is driven by prediction errors

Kamin, Rescorla, Wagner



Value function: the sum of all future reward

$$V(t) = r(t) + r(t+1) + r(t+2) + \cdots$$

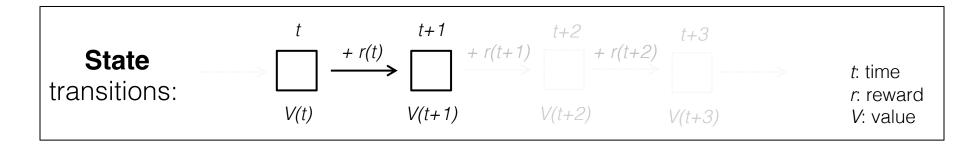
$$V(t+1)$$

$$\hat{V}(t) = r(t) + \hat{V}(t+1)$$

Temporal difference (TD) error

$$\delta = r(t) + \hat{V}(t+1) - \hat{V}(t) \qquad \Rightarrow \qquad \\ \hat{V}(t) \leftarrow \hat{V}(t) + \alpha \cdot \delta \quad (\alpha: \text{ learning rate})$$

(Sutton, 1988; Sutton & Barto, 1998; Montague et al., 1996; Schultz et al., 1997)



Value function: the sum of all future reward

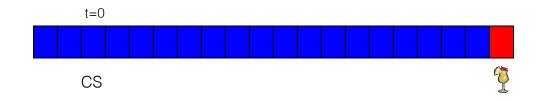
$$V(t) = r(t) + \frac{\gamma \cdot r(t+1) + \frac{\gamma^2}{2} \cdot r(t+2) + \cdots}{\gamma \cdot V(t+1)}$$

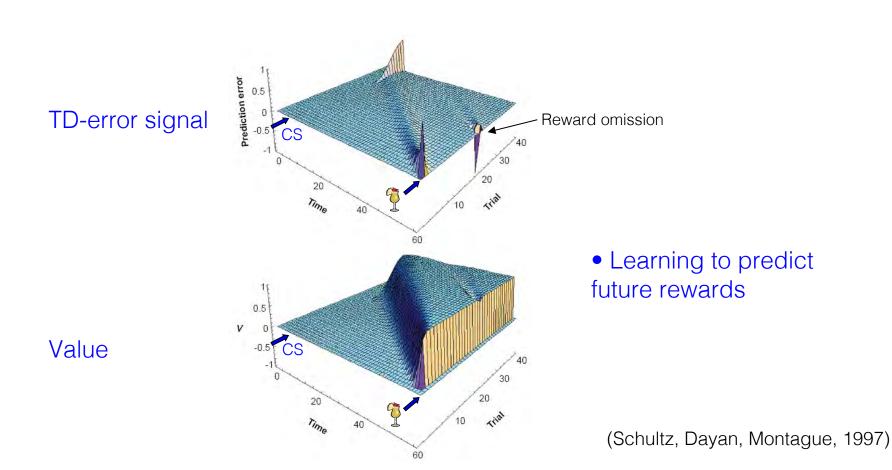
$$\hat{V}(t) = r(t) + \frac{\gamma}{2} \cdot \hat{V}(t+1)$$

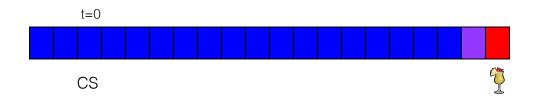
Temporal difference (TD) error

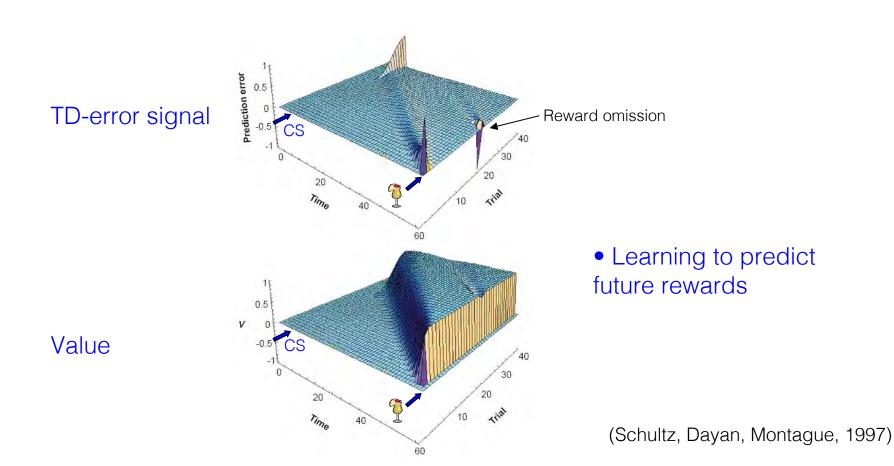
$$\delta = r(t) + \gamma \cdot \hat{V}(t+1) - \hat{V}(t) \qquad \Rightarrow \qquad \begin{array}{c} \text{Update } V(t) \\ \\ \hat{V}(t) \leftarrow \hat{V}(t) + \alpha \cdot \delta \quad \text{($\alpha$: learning rate)} \end{array}$$

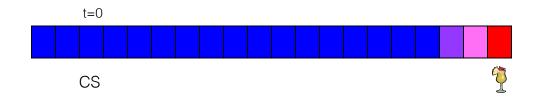
(Sutton, 1988; Sutton & Barto, 1998; Montague et al., 1996; Schultz et al., 1997)

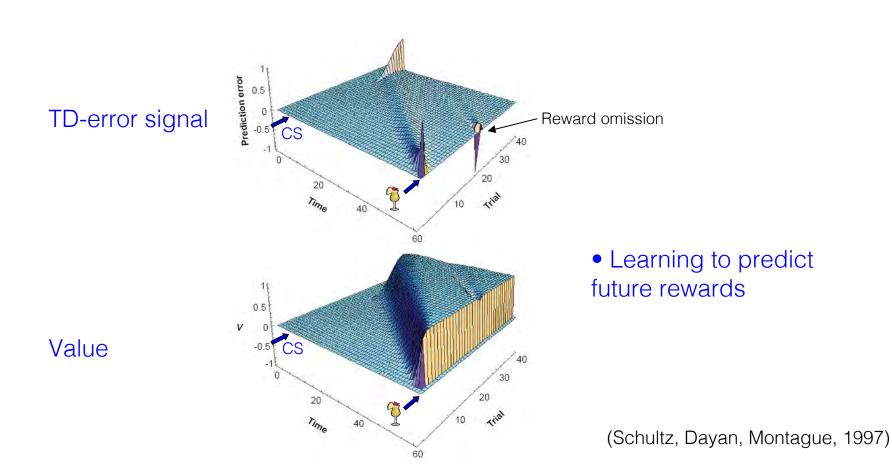


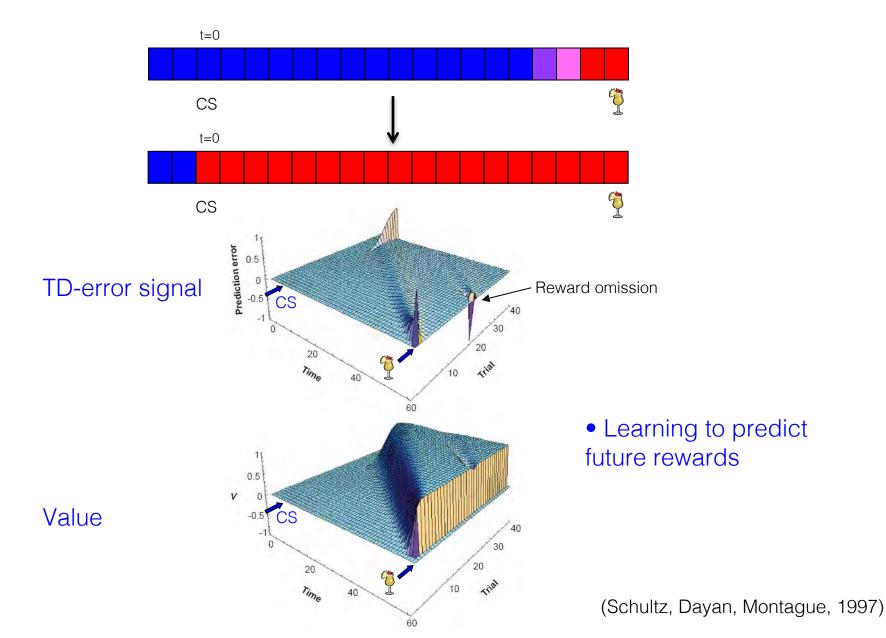


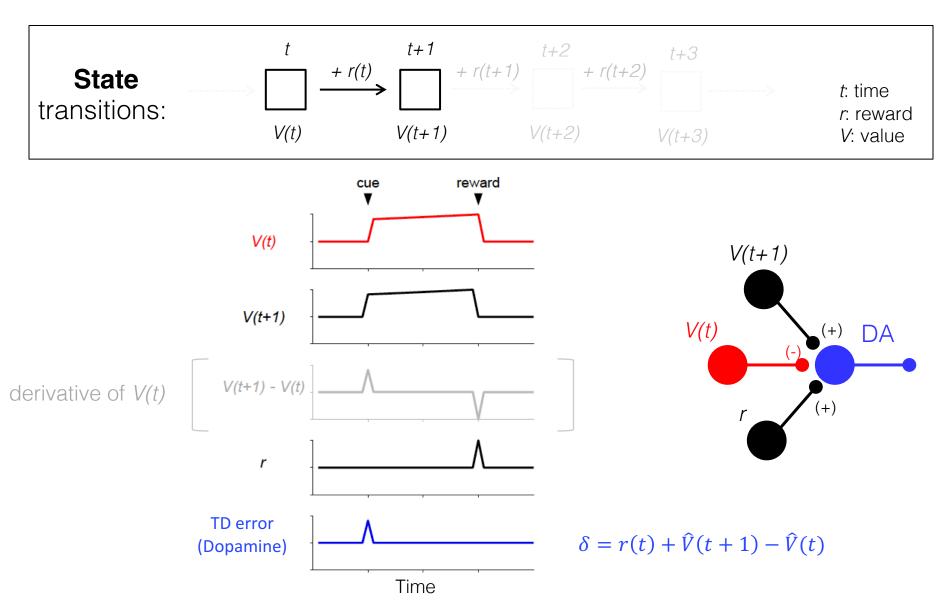




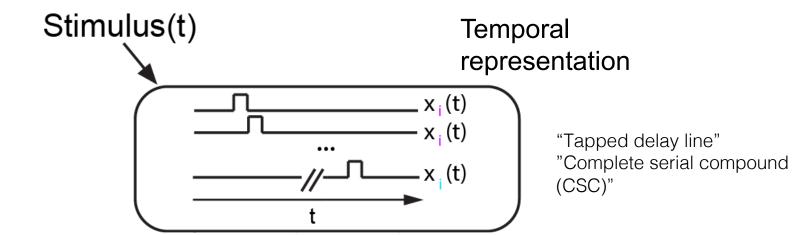


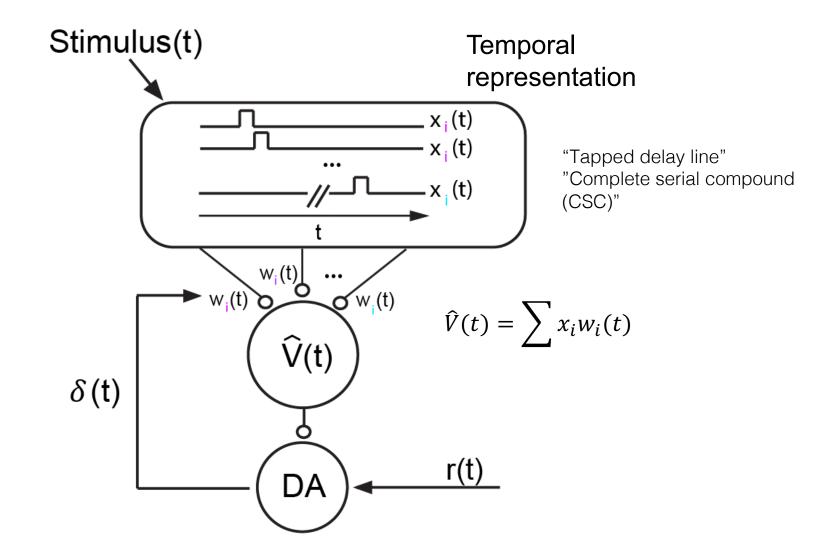






(Sutton, 1988; Sutton & Barto, 1998; Montague et al., 1996; Schultz et al., 1997, Watabe-Uchida et al., 2017)



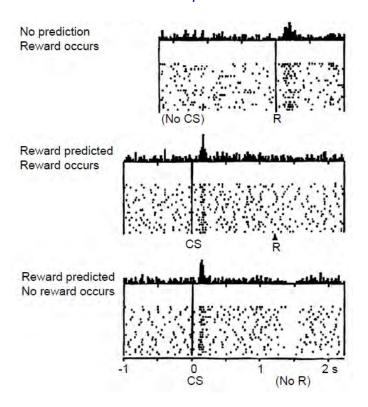


(Sutton, 1988; Sutton & Barto, 1998; Montague et al., 1996; Schultz et al., 1997)

### A Neural Substrate of Prediction and Reward

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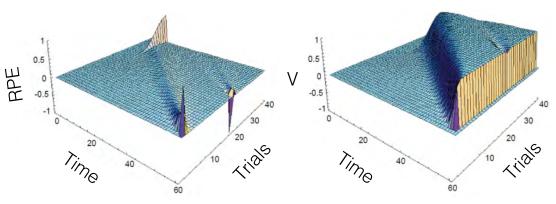


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Animal learning theory
 Learning is driven by prediction errors
 Kamin, Rescorla, Wagner

### Dopamine as a TD error

- Magnitude
- Probability
- Temporal discounting
- Temporal uncertainty
- Long term value
- Cost / efforts (?)
- Safety
- Axiomatic proof

### Dopamine as a TD error

- Supporting evidence
- Minor problems
- Serious problems

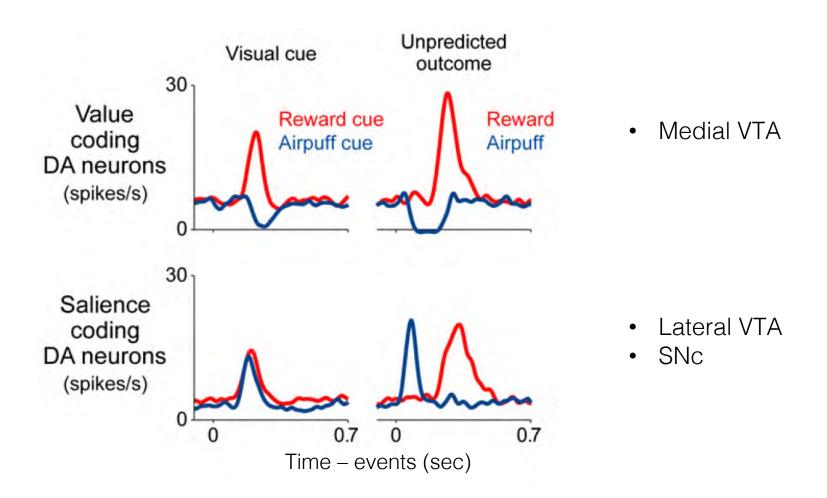
### Topics

- A mouse model for studying dopamine RPE
- Do all dopamine neurons signal RPEs?
- What is the "state" in reinforcement learning?
- How are RPEs computed?
- Diversity of dopamine neurons

### Topics

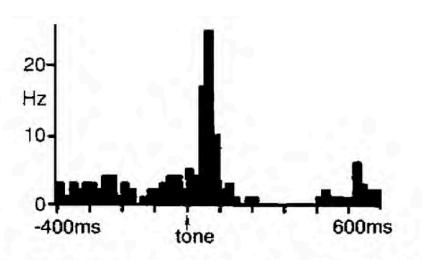
- A mouse model for studying dopamine RPE
- Do all dopamine neurons signal RPEs?
- What is the "state" in reinforcement learning?
- How are RPEs computed?
- Diversity of dopamine neurons

### The problem of punishment



(Matsumoto & Hikosaka, 2008; Bromberg-Martin, Matsumoto, Hikosaka, 2010)

### Novel stimuli activate some dopamine neurons



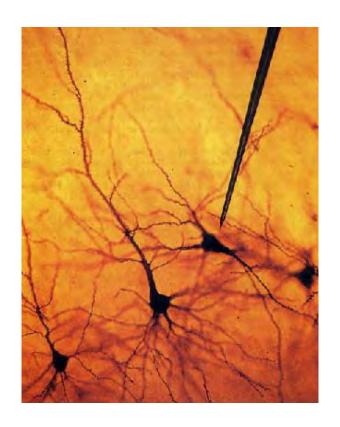
(adapted from Kakade and Dayan, 2002)

Fig. 6. Novelty response with phasic activation and depression. This shows a histogram of the activity of a single dopamine cell in cat VTA in response to repetitions of an initially novel tone. This neuron shows a clear pattern of activation and depression in response to the stimulus. Adapted from Horvitz, Steward, and Jacobs (1997).

Attempts to incorporate novelty response into the value framework

- Potential reward or novelty itself is rewarding
- Positive value of exploration

# "The cell identification problem"



Extracellular recording

### "The cell identification problem"

Waveforms, spontaneous firing rates, pharmacology

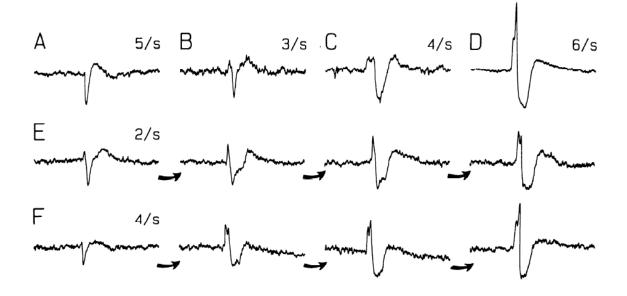


(Grace and Bunney, 1983; also see Ungless and Grace, 2012)

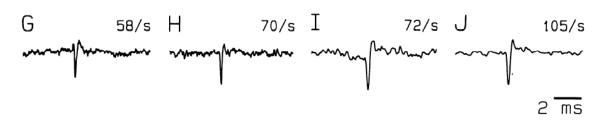
 Recent studies indicate diverse waveforms in dopamine neurons (e.g. Margolis et al., 2006; Lammel et al. 2008)

### "The cell identification problem"

Dopamine

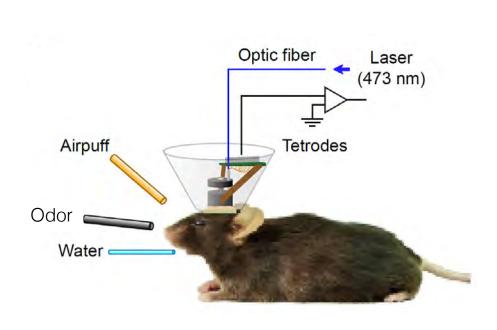


Non-dopamine

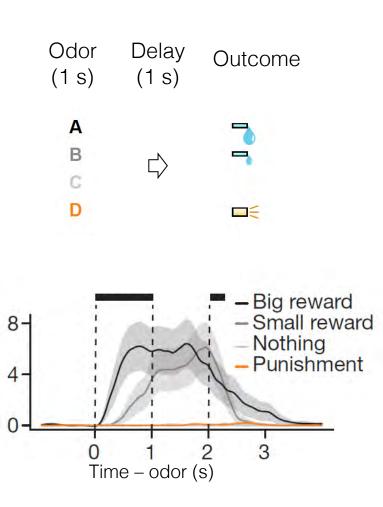


 Spike waveforms differ not only by neuron types but also relative locations to electrode

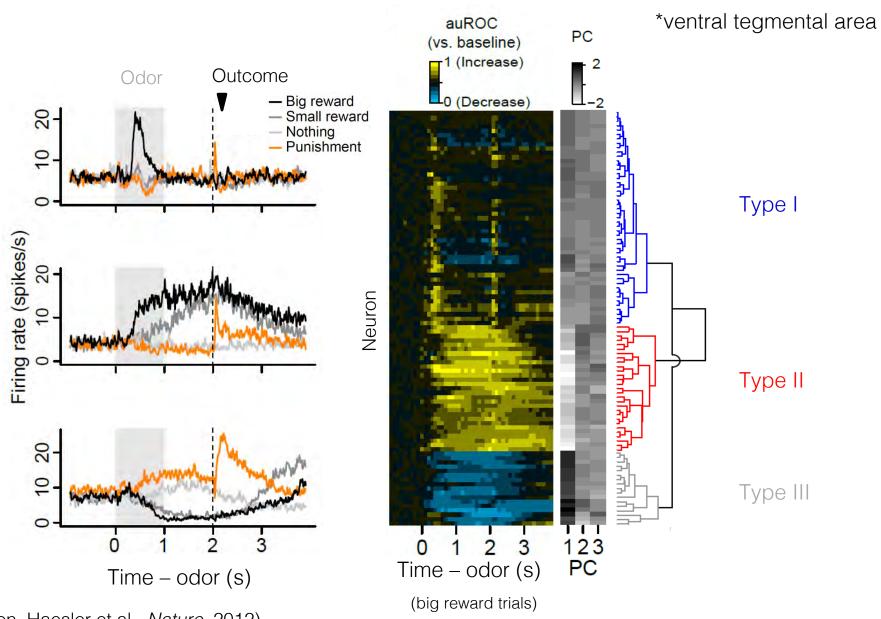
#### Odor-value association task in mice



- Head-restrained mice
- Efficient training (1-2 days)
- Electrophysiology in behaving mice

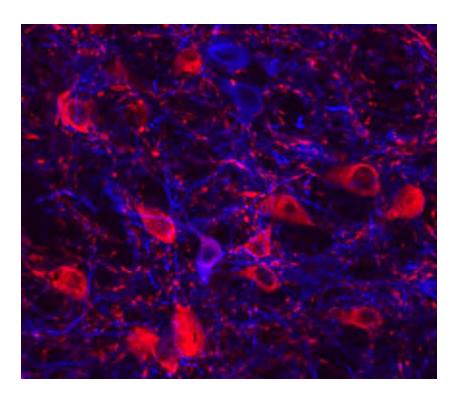


### Three response types in VTA\*



(Cohen, Haesler et al., Nature, 2012)

### VTA contains multiple neuron types



Dopamine neurons (55-65 %)

GABA neurons (30-40 %)



### "The recording problem"



It is one of the peculiar features of most modern neurophysiology that the experimentalist...seldom knows which type of neuron he or she is listening to... It is common for experimentalist to record that, say, 25% of the neurons studied behave in a particular way, 37% in a different way and a further 15% in a third way... There is no indication where these different sets of neurons are sending their information, let alone exactly what type of neuron they are. This is not science but rather natural history. Rutherford would probably have called it stamp collecting.

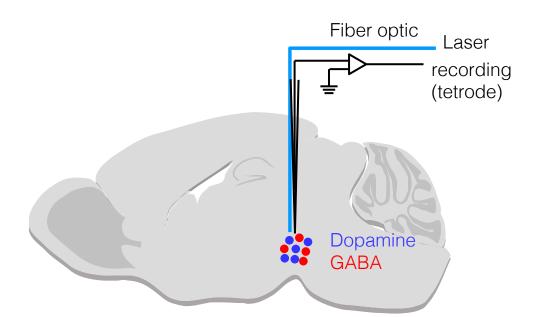
(Francis Crick, 1999, The impact of molecular biology on neuroscience)

### **Ernst Rutherford**



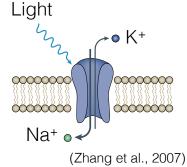
All science is either physics or stamp collecting

#### Optogenetic identification of neuron types



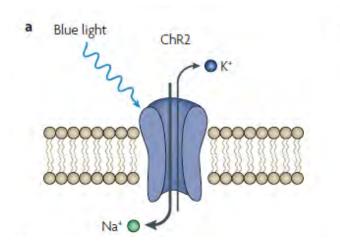
Channelrhodopsin-2 (ChR2) in dopamine neurons

- DAT-Cre (dopamine)
- Vgat-Cre (GABA)
- AAV-FLEX-ChR2



# Optogenetics

### Channelrhodopsin-2

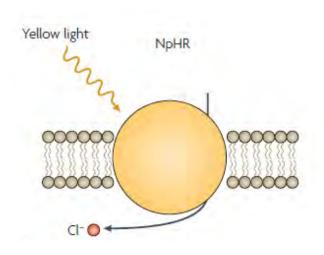


Light-gated ion-channel

Cation channel (H+, Na+, K+, and Ca2+)

from green algae

#### Halorhodopsin



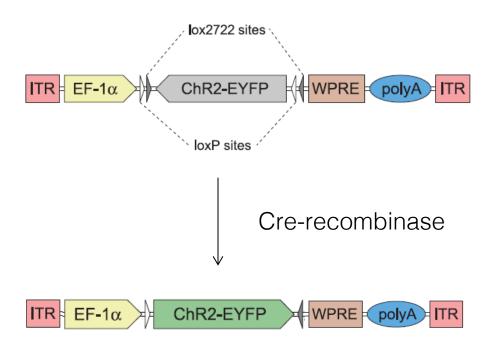
Light-activated Cl<sup>-</sup> pump from halobacteria

Activation

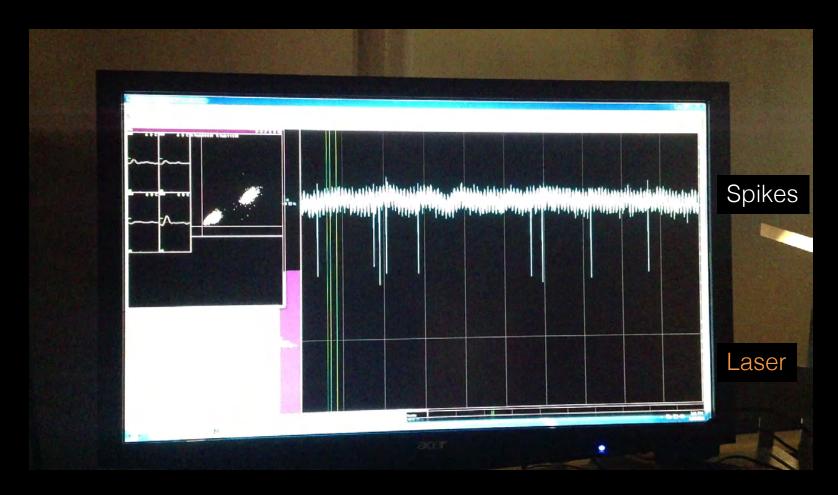
Inactivation

### Cre/loxP recombination system

- Transgenic mice: Cre-recombinase is expressed in a specific neural population.
- Inject adeno-associated virus carrying floxed-channerhodopsin-2 (ChR2)



## Optogenetic identification of neuron types

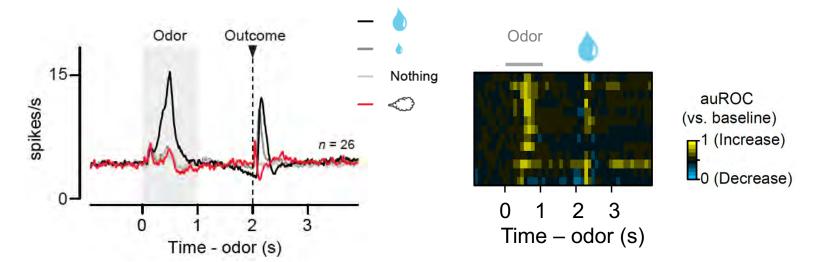


#### Criteria

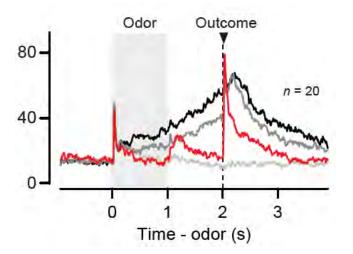
- 1) Latency < 2-4 ms
- 2) Follow high frequency stimulation
- 3) Spike shapes are almost identical between light-evoked and spontaneous spikes

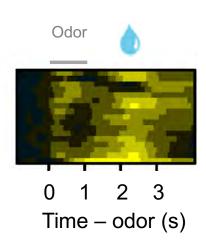
## Neuron-type-specific signals in VTA

Dopamine neurons

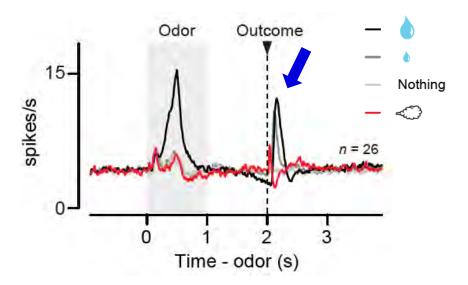


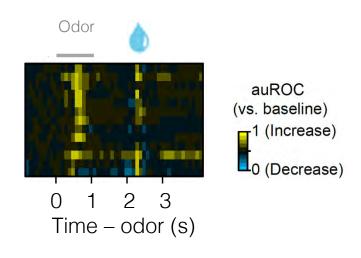
GABA neurons



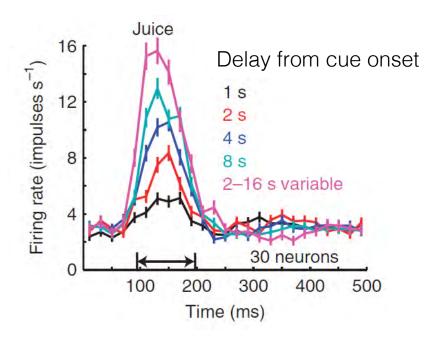


(Cohen, Haesler et al., Nature, 2012)





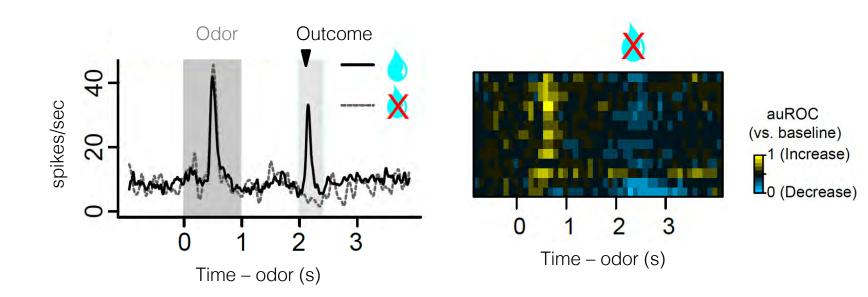
#### Effect of delays



Delay → reduced reward predictability → increased dopamine RPEs

(Fiorillo, Newsome and Schultz, 2008; also see, Kobayashi et al., 2008)

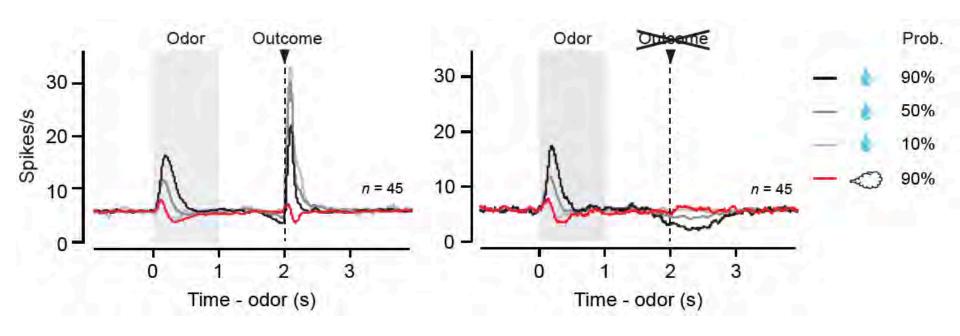
Reward omission (negative prediction error)



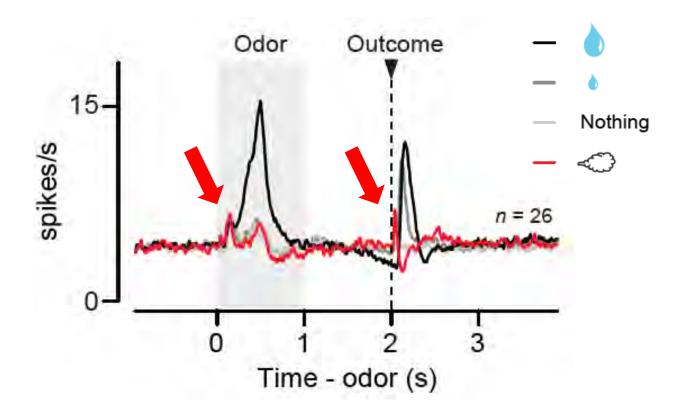
Omission of reward causes suppression of firing.

## Recording from optogenetically-identified dopamine neurons

#### RPE coding by VTA dopamine neurons

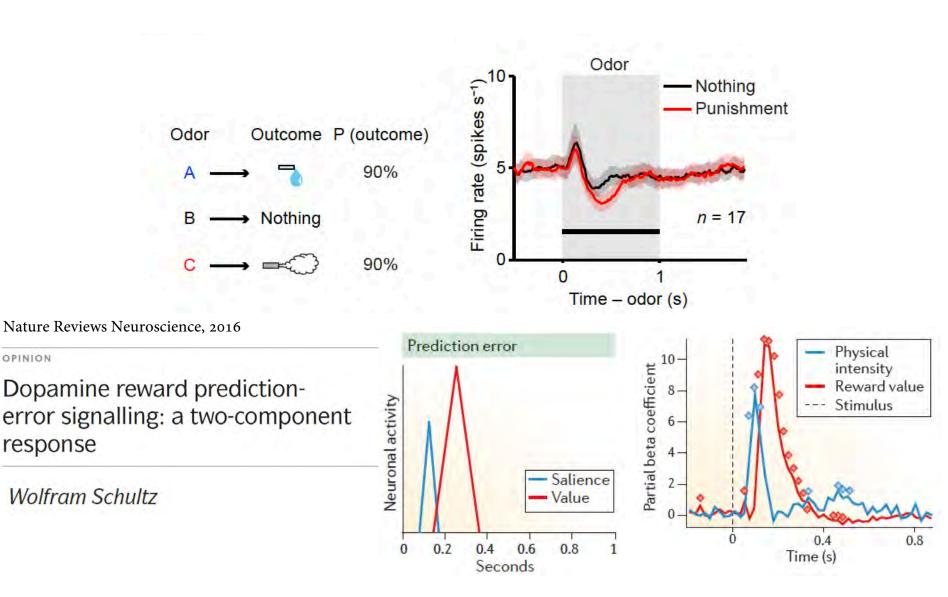


#### What about aversive stimuli?



Biphasic dopamine response to air puff or air puff-predictive cues

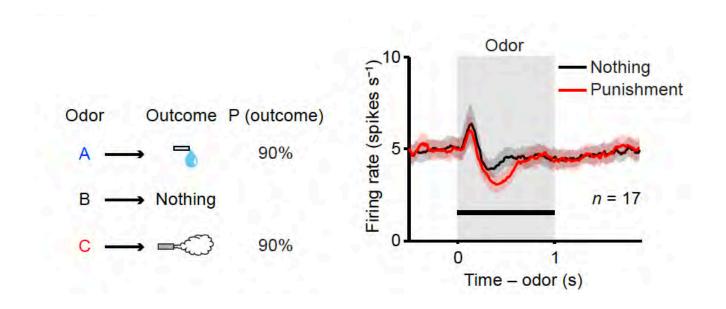
## Context-dependency of dopamine aversion response



OPINION

(Matsumoto, Tian, Uchida and Watabe-Uchida, eLife, 2016)

## Context-dependency of dopamine aversion response

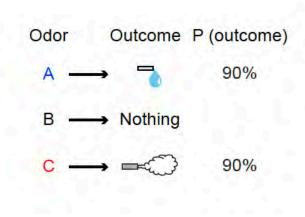


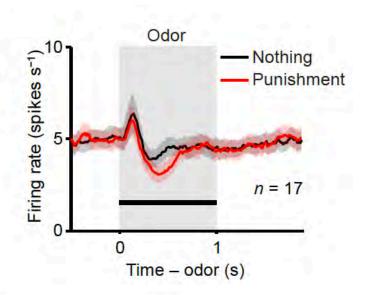
Kobayashi and Schultz, 2014

Reward contexts extends dopamine signals to unrewarded stimuli

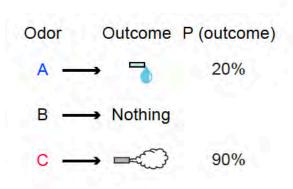
## Context-dependency of dopamine aversion response

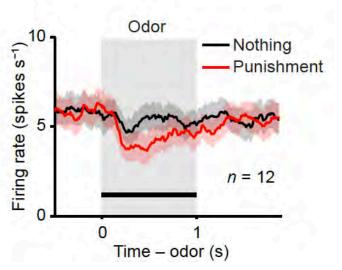
High reward context





Low reward context



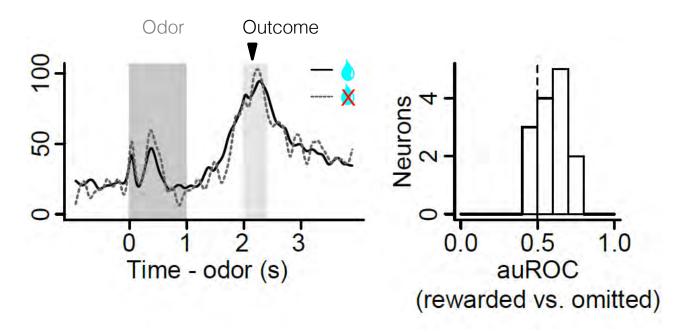


(Matsumoto, Tian, Uchida and Watabe-Uchida, eLife, 2016)

What do GABA neurons signal?

## VTA GABA neurons signal reward expectation

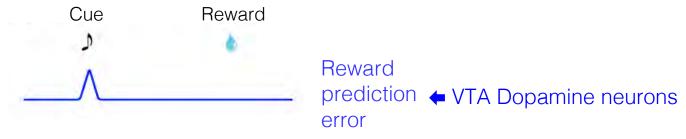
#### GABA neuron



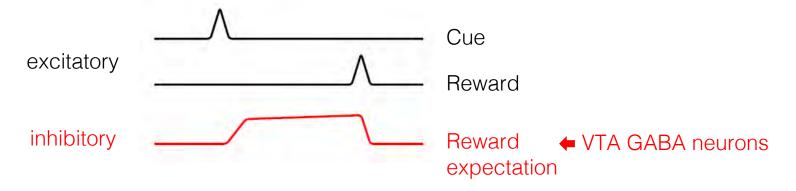
- Delivery of reward has little impact on firing.
- The activity reflects the expected time of reward.

## VTA GABA neurons may provide the reward expectation signal to dopamine neurons

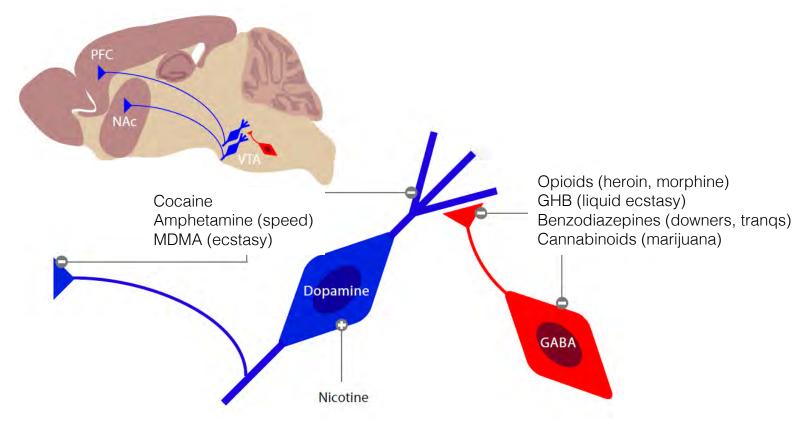
Output (dopamine neurons)



Model (inputs to dopamine neurons)

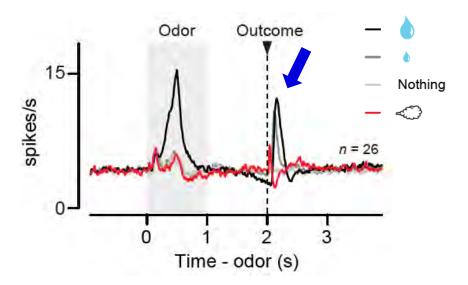


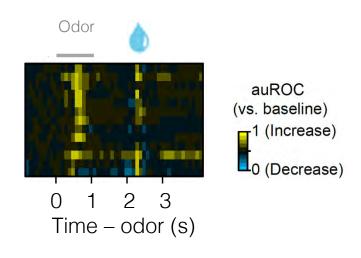
## Addiction as impaired prediction error signaling



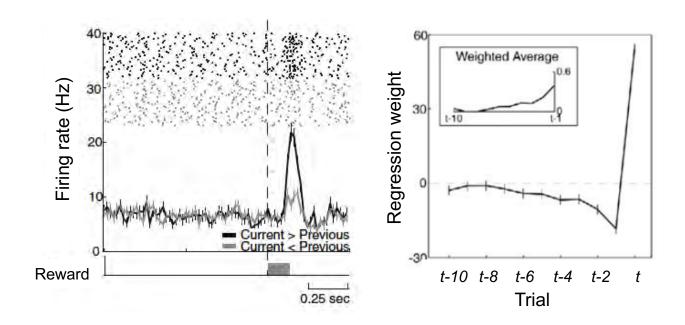
(Luscher & Malenka, 2011; Hyman, Malenka & Nestler, 2006)

- Addictive drugs inhibit VTA GABA neurons
- Persistent reinforcement signals by addictive drugs (Redish, 2004)





## Dopamine = Present reward – weighted sum of previous rewards



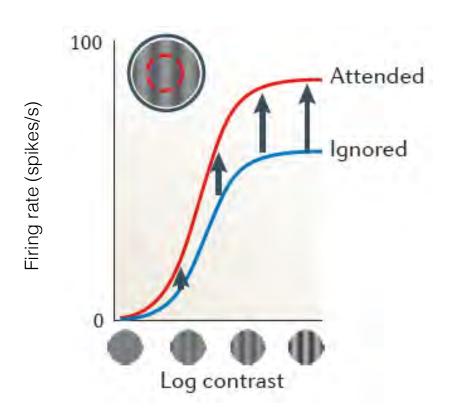
#### Regression analysis

$$FR = b_0 + b_1 r_t + b_2 r_{t-1} + b_3 r_{t-2} + \cdots$$

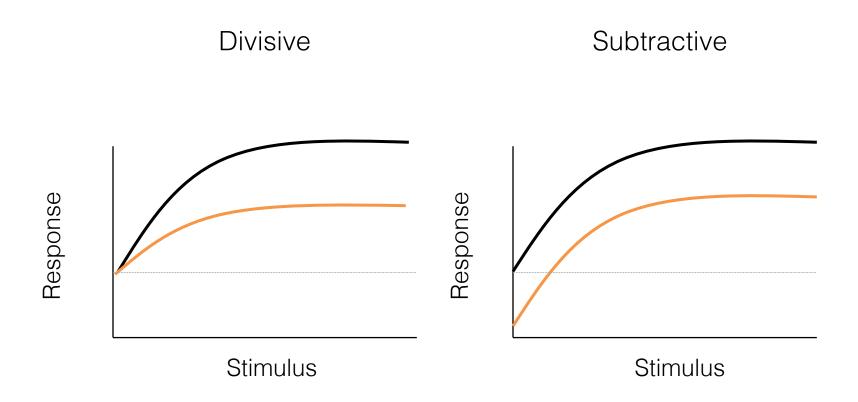
FR: firing rate of dopamine neurons

r<sub>t</sub>: reward size at trial tb: regression weight

## Divisive (multiplicative) "gain" change

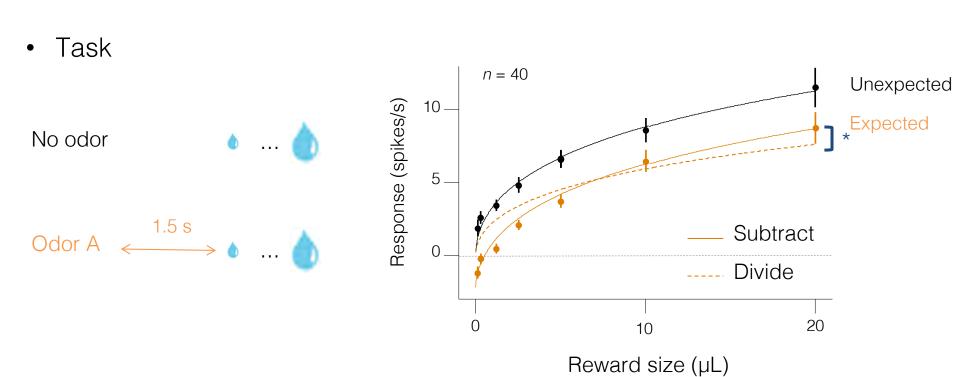


## Testing computations



## Reward expectation triggers subtraction

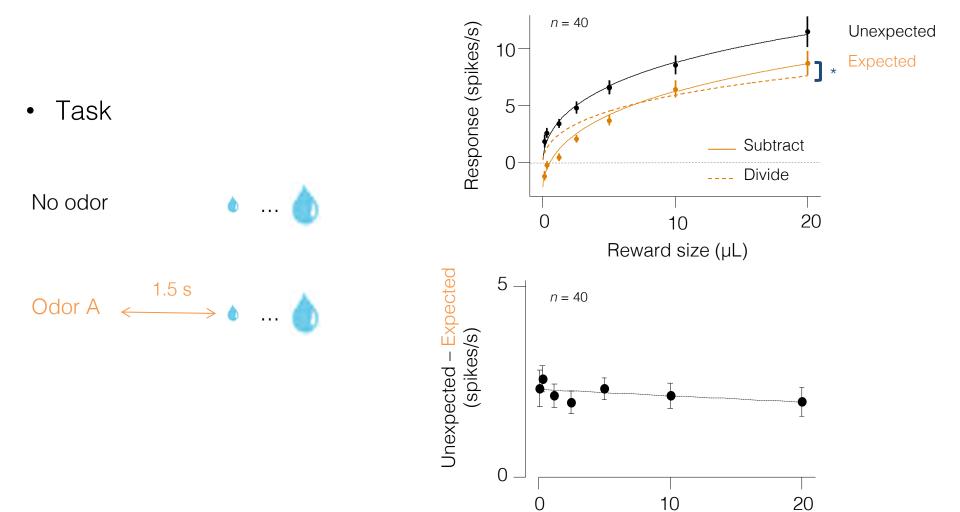
(0-600ms after reward onset)



\*P < 0.001, bootstrap to compare model fits

(Eshel, Bukwich, Rao, Hemmelder, Tian and Uchida, Nature, 2015)

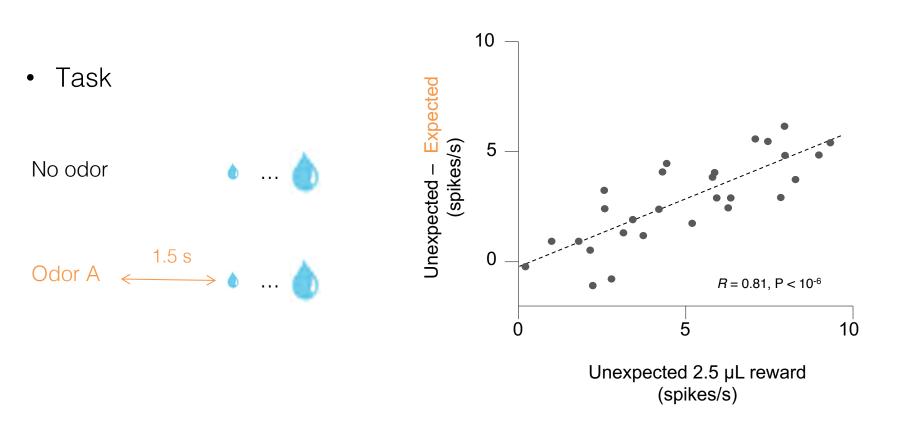
## Reward expectation triggers subtraction



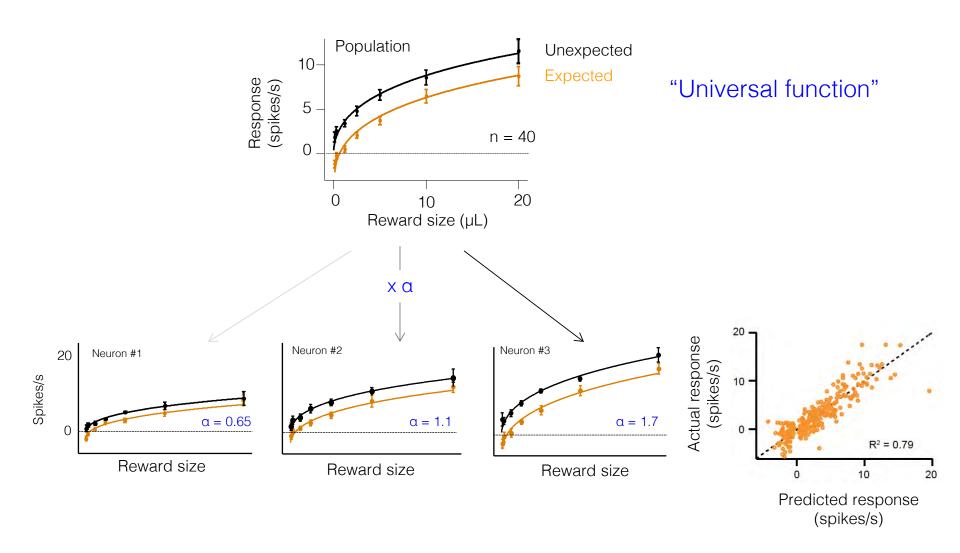
Reward size (µL)

(Eshel, Bukwich, Rao, Hemmelder, Tian and Uchida, Nature, 2015)

## Subtraction is **scaled** by reward response



## Dopamine neurons follow a universal template

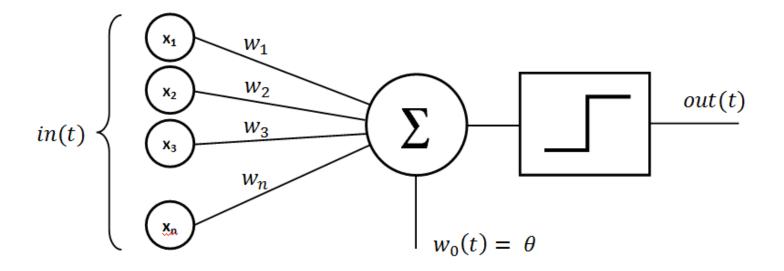


(Eshel, Bukwich, Tian and Uchida, Nature Neurosci. 2016)

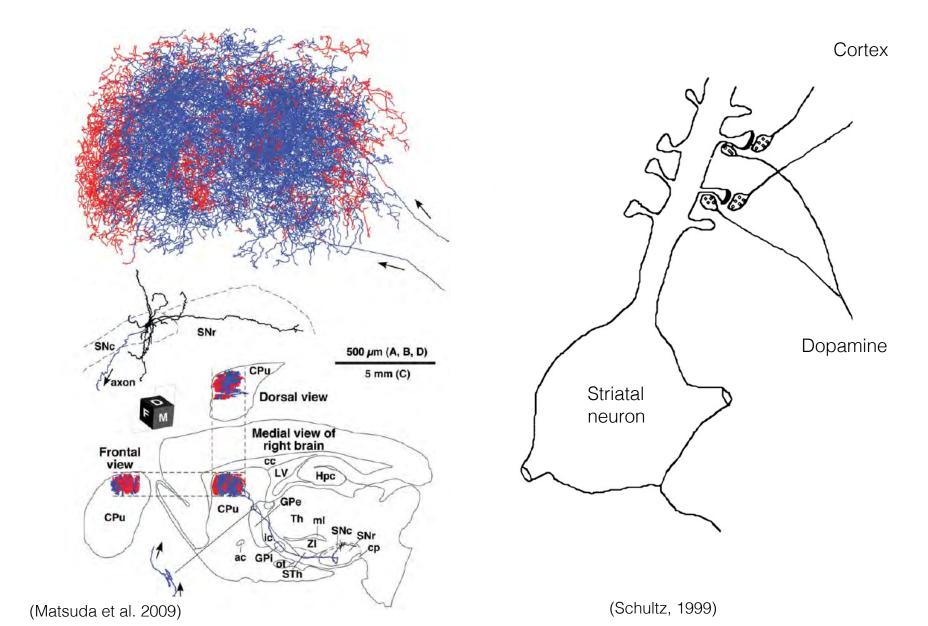
## Summary

- Nearly all dopamine neurons exhibited phasic excitations to rewardpredictive cues and reward.
- Some dopamine neurons show biphasic responses to aversive events but these responses are diminished in low reward contexts.
- VTA GABA neurons signal reward expectation, which can suppress dopamine reward responses when reward is expected.
- Reward expectation reduces dopamine reward responses in a subtractive fashion.
- Subtraction was scaled by a neuron's responsiveness to reward. This
  relationship may naturally arise from balanced excitation and
  inhibition.

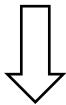
## Population coding



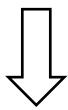
## What is a good teaching signal? Many synapses, each synapse



## Common inputs balanced excitation/inhibition

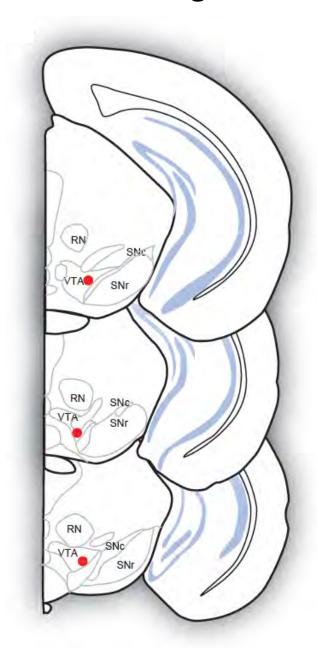


Homogeneity of dopamine signals



Consistency

## Recording sites



## **Topics**

- A mouse model for studying dopamine RPE
- Do all dopamine neurons signal RPEs?
- What is the "state" in reinforcement learning?
- How are RPEs computed?
- Diversity of dopamine neurons

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Wolfram Schultz, Peter Dayan, P. Read Montague\*

Phasic dopamine

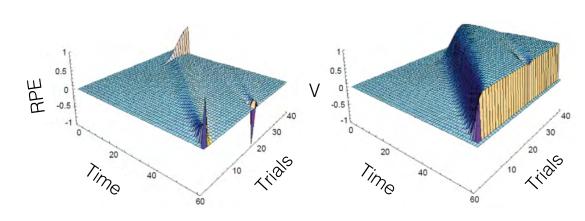
No prediction Reward occurs Reward predicted Reward occurs Reward predicted No reward occurs (NoR) CS

Temporal difference (TD) learning theory

$$V(t) = E[\gamma^{0}r(t) + \gamma^{1}r(t+1) + \gamma^{2}r(t+2) + \cdots]$$
 (1)

$$V(t) = E[r(t) + \gamma V(t+1)] \qquad (2)$$

$$\delta(t) = r(t) + \gamma \hat{V}(t+1) - \hat{V}(t) \quad (3)$$

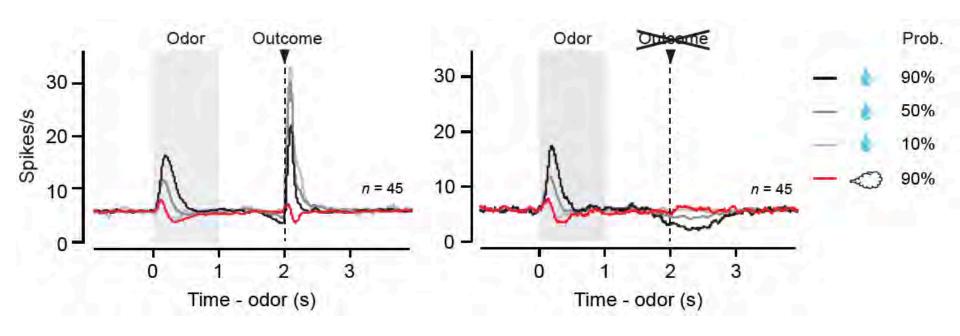


Animal learning theory

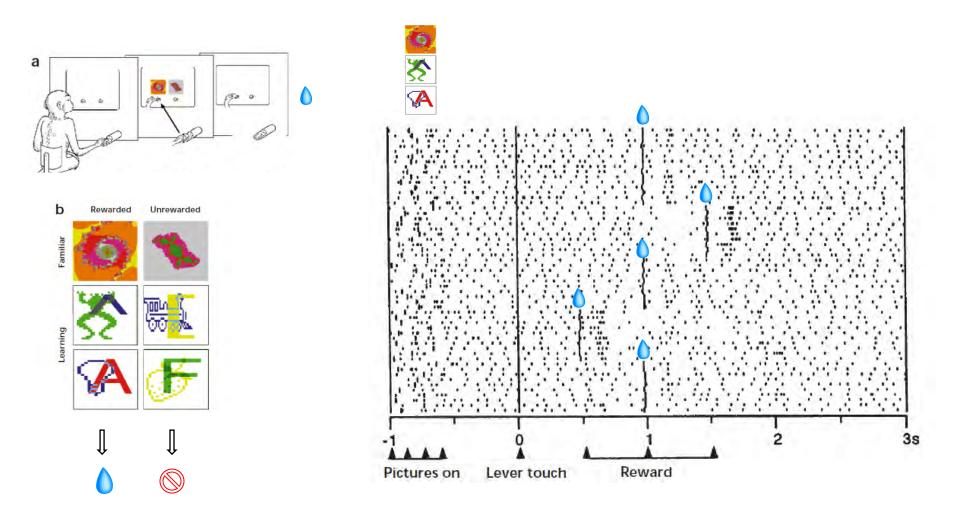
Kamin, Rescorla, Wagner

## Recording from optogenetically-identified dopamine neurons

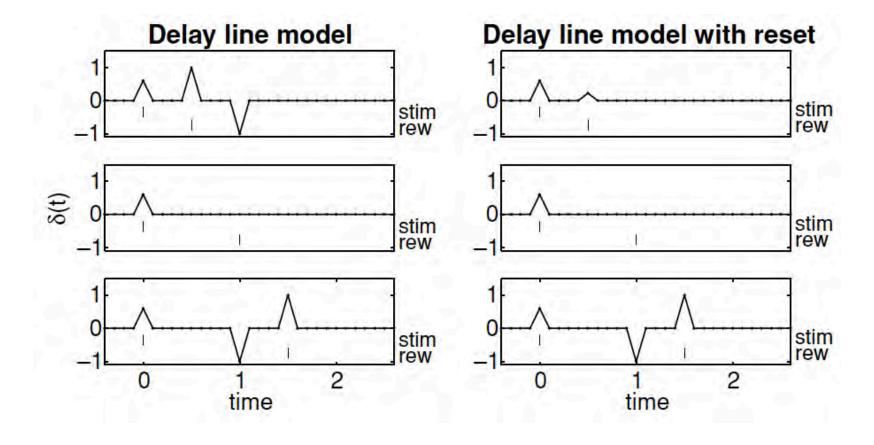
#### RPE coding by VTA dopamine neurons



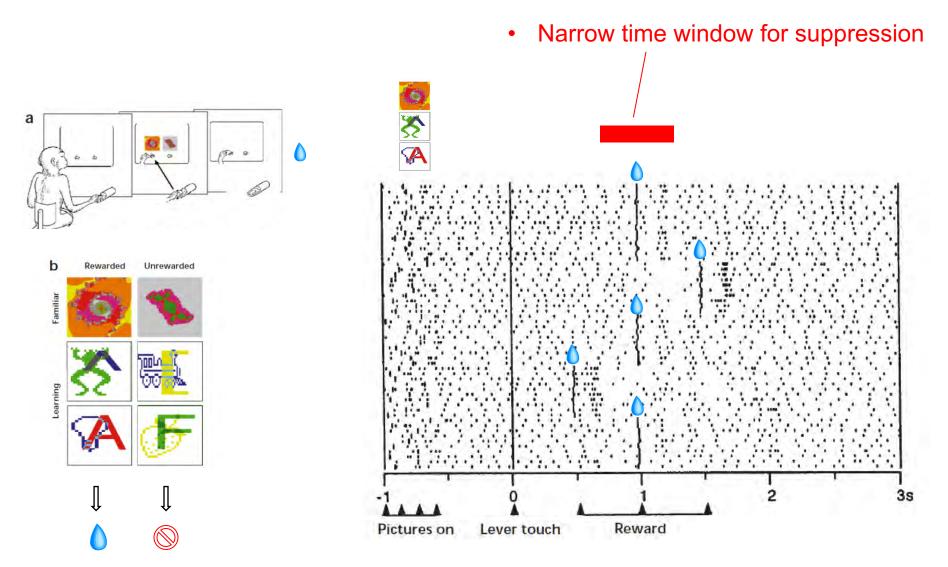
# Dopamine neurons exhibit exquisite sensitivity to reward expectation over time



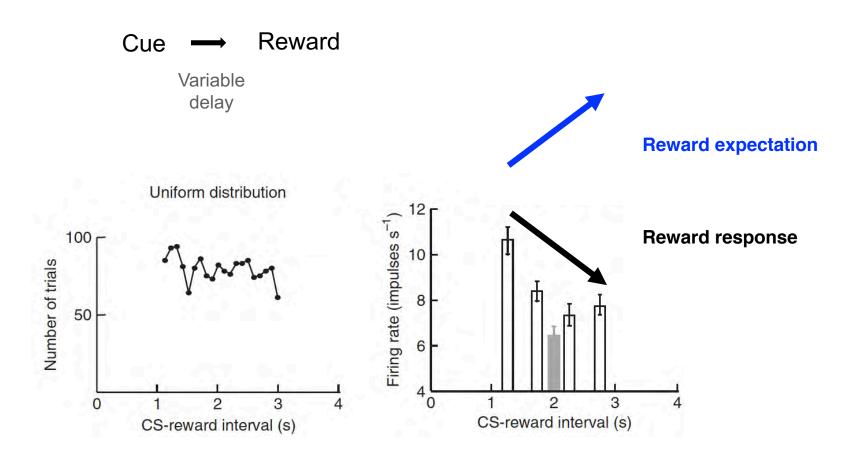
## The TD model does not explain Hollerman & Schultz (2008)



# Dopamine neurons exhibit exquisite sensitivity to reward expectation over time



## Dopamine response in a variable delay condition



## Expectation over time follows hazard rate

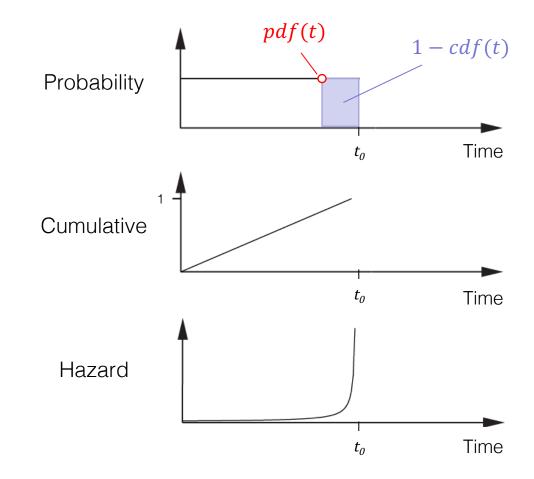
 Hazard rate: Likelihood that an event will occur given that it has not yet happened.

$$h(t) = \frac{pdf(t)}{1 - cdf(t)}$$

h(t): Hazard rate

pdf(t): Probability density

cdf(t): Cumulative distribution



### Timing sensitivity of dopamine neurons

- Dopamine "dip" at the time of expected reward
  - Schultz, Dayan, Montague (1997)
  - Hollerman and Schultz (1998)
  - Lateral habenula: Matsumoto and Hikosaka (2008), Tian and Uchida (2015)
- Hazard-like modulation of dopamine RPE
  - Nakahara et al. 2004
  - Fiorillo, Newsome, Schultz, 2008
  - Nomoto et al, 2010
  - Pasquereau and Turner, 2015

### Question

- What is the shape of the expectation function across time?
- Is hazard rate a good explanation for it?
- Which brain areas are involved in computing reward expectation across time?

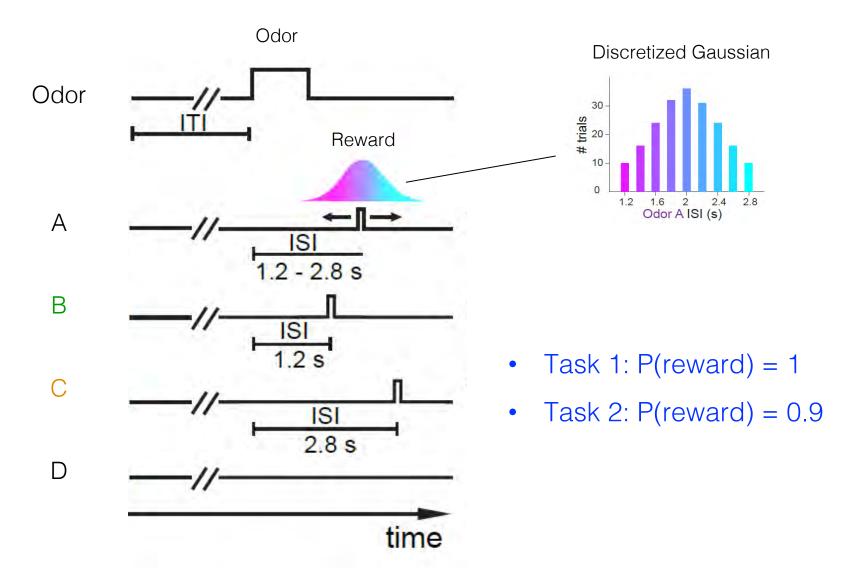


Clara Starkweather

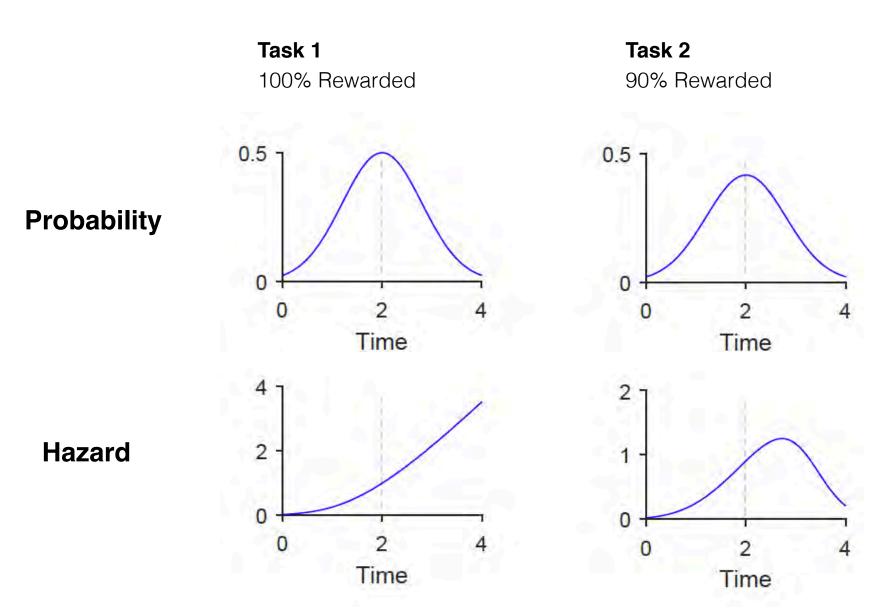


Samuel Gershman

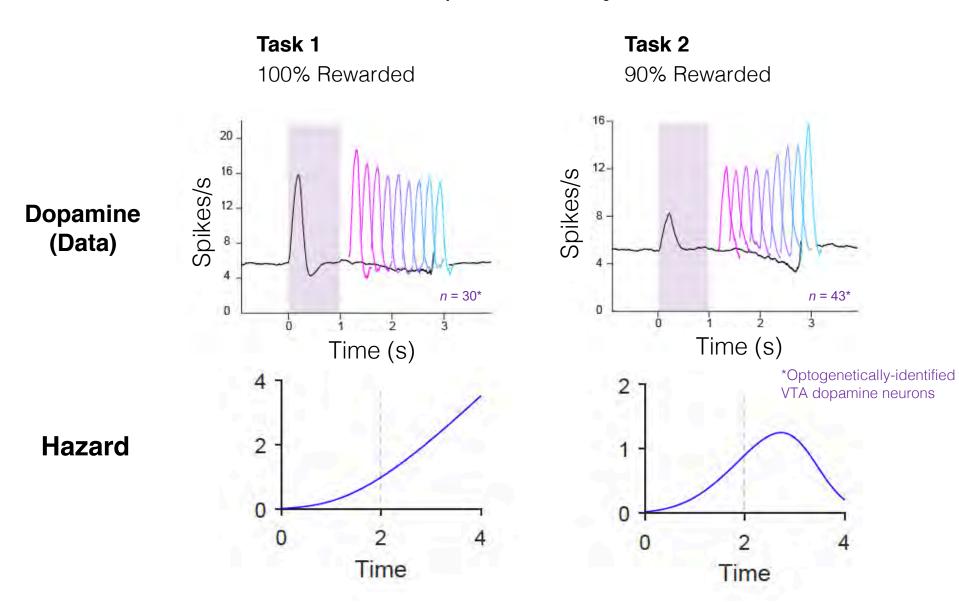
## Task



### Prediction



### Data cannot be explained by hazard rate



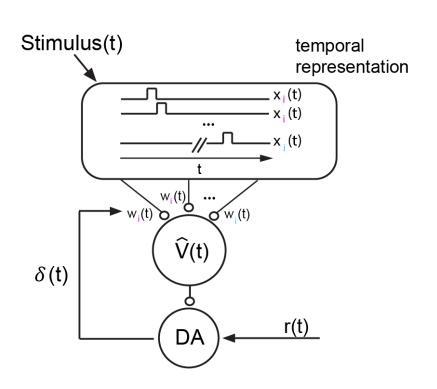
### Can a simple learning algorithm explain our data?

- Temporal Difference (TD) learning
  - Moore et al. (1998), Sutton and Barto (1990), Montague et al. (1996), Schultz, Dayan, Montague (1997)
  - Keeps track of time after stimulus onset as a series of time steps
    - "Complete serial compound (CSC)"

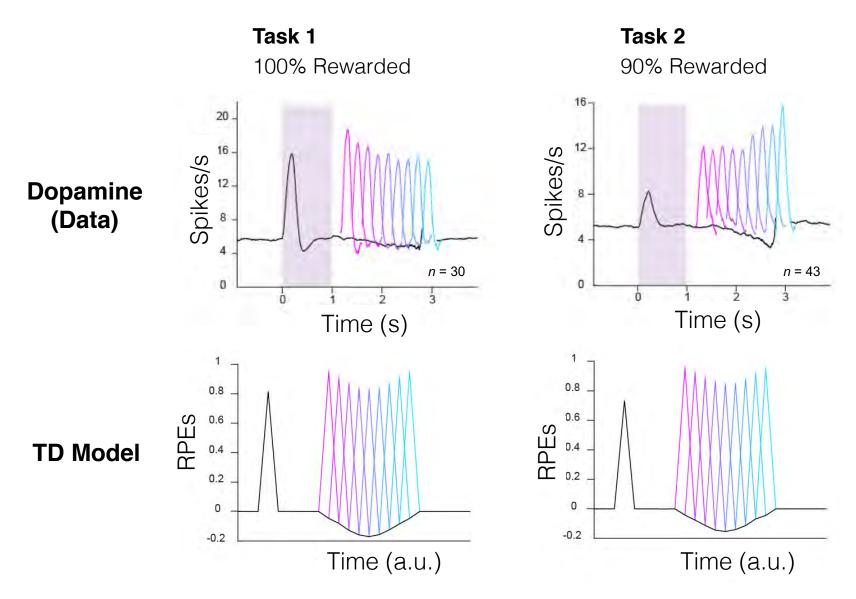
$$V(t) = r(t) + \gamma^{1}r(t+1) + \gamma^{2}r(t+2) + \cdots$$

$$\hat{V}(t) = r(t) + \gamma \hat{V}(t+1)$$

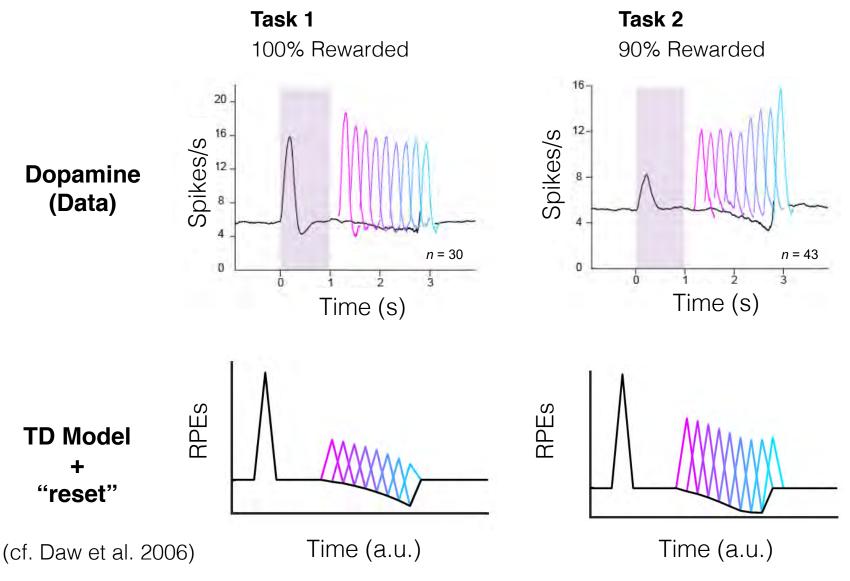
$$\delta(t) = r(t) + \gamma \hat{V}(t+1) - \hat{V}(t)$$



### Classic TD learning cannot explain our data



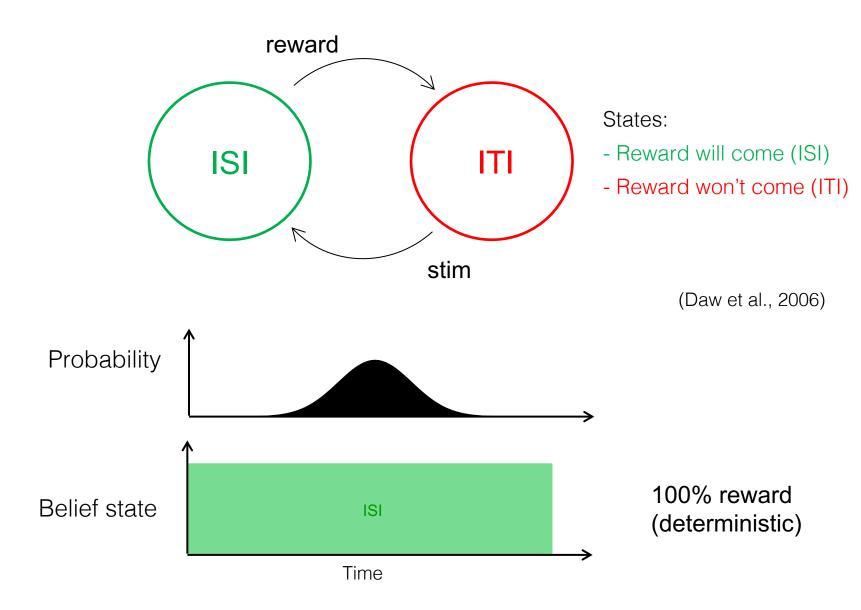
# TD learning with CSC with reset generates hazard-like dynamics



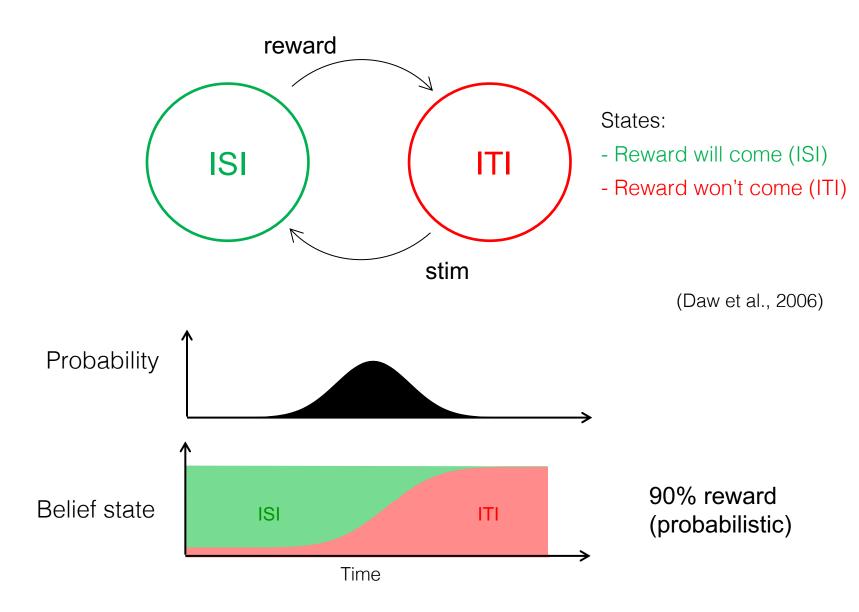
### Can a proposed modification to TD learning explain our data?

- Animals have to infer which "state" they are in.
- Proposed amendment
  - TD + belief state (rather than CSC)
  - Belief state = p(state | observations)
  - Daw et al, 2006; Rao et al, 2010
- RL models must operate on a belief state

### Belief state model



### Belief state model

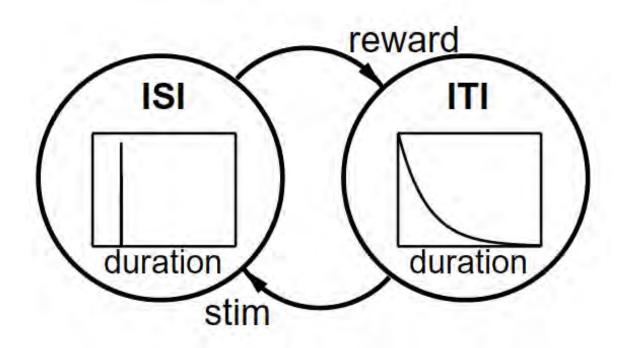


## Expectation across time

- Dynamic Bayesian Inference
  - Prior knowledge



## A semi-Markov model of trace conditioning

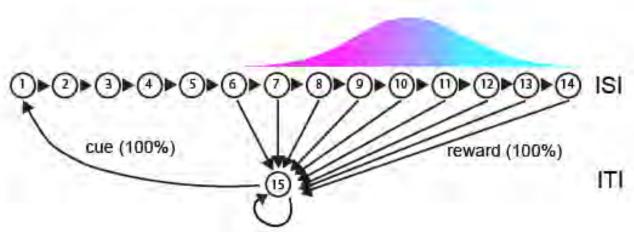


- State transitions
- Dwell time distribution

### Belief state TD model

Partially observable Markov decision process

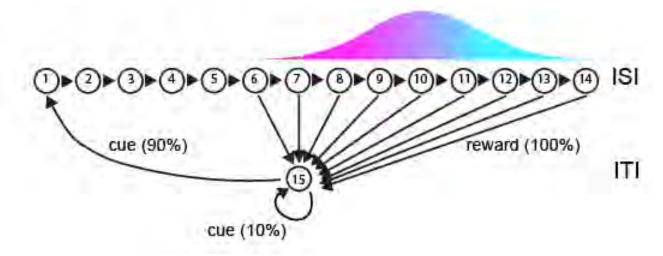
Task 1 (100% reward)



### Belief state TD model

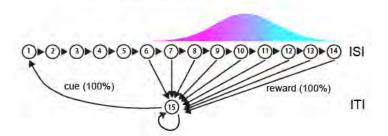
Partially observable Markov decision process

Task 2 (90% reward)

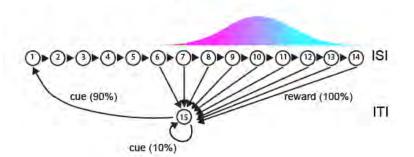


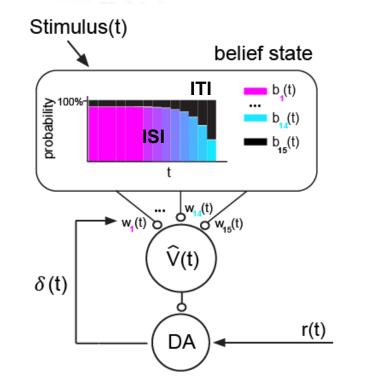
### Belief state TD model

Task 1 100% Rewarded

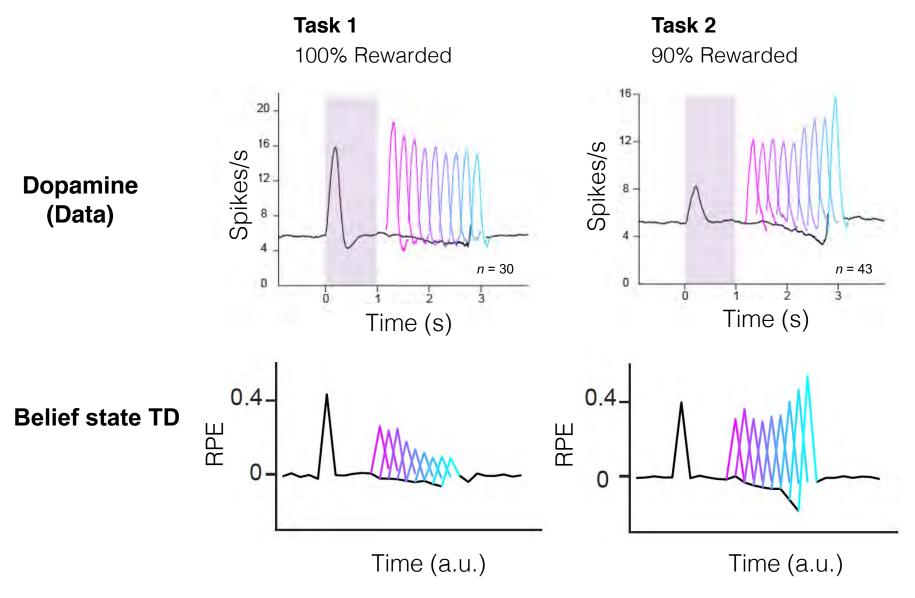


**Task 2** 90% Rewarded

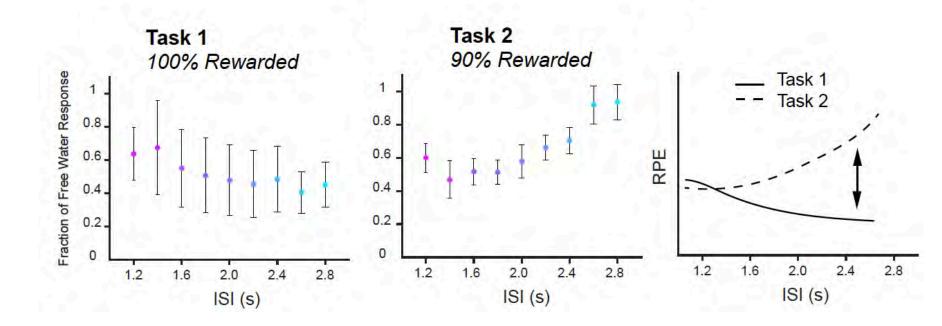




### Belief state TD model captures data

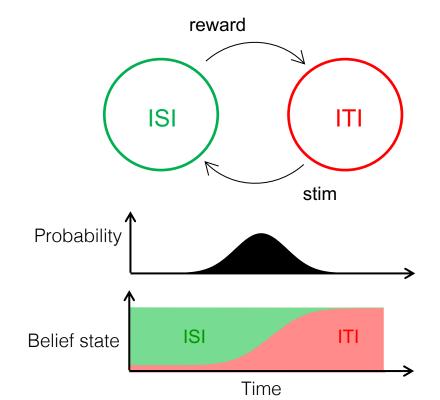


Normalized by the responses to unexpected reward



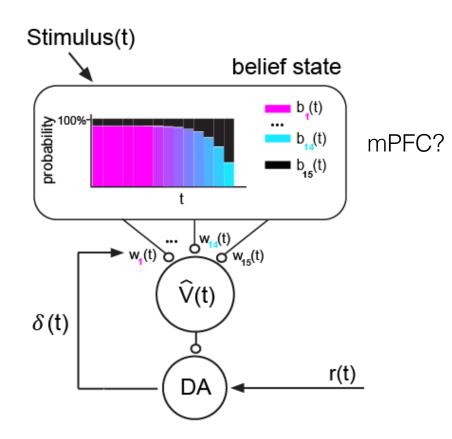
### Summary

- Dopamine RPEs are shaped by
  - Interval timing (hazard rate)
  - Hidden state inference (belief state)

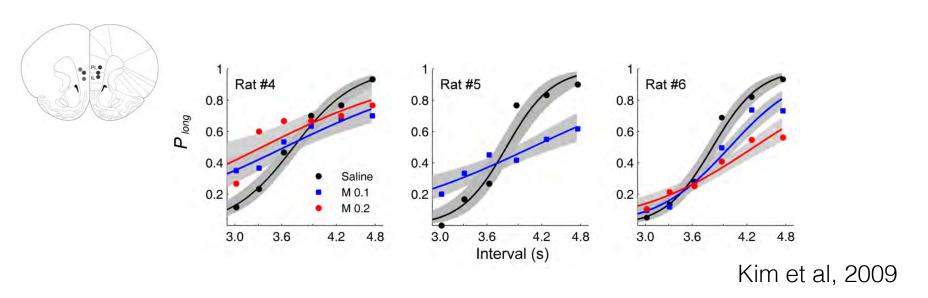


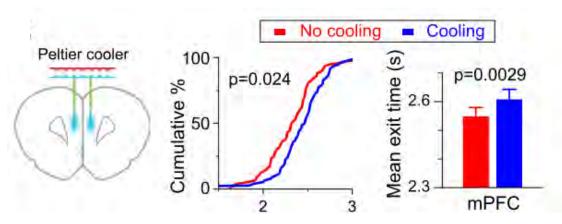
### What brain area conveys belief state to dopamine system?

- Hidden state inference tied to timing
  - Candidate area: mPFC
    - Kim et al, 2009; 2013
    - Xu et al, 2014

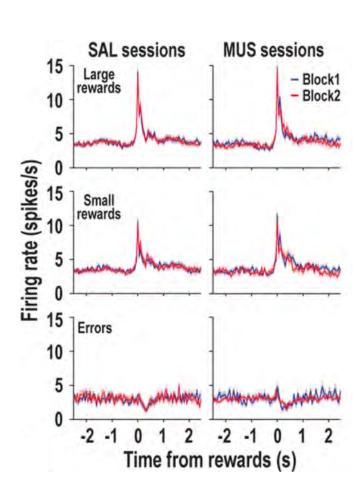


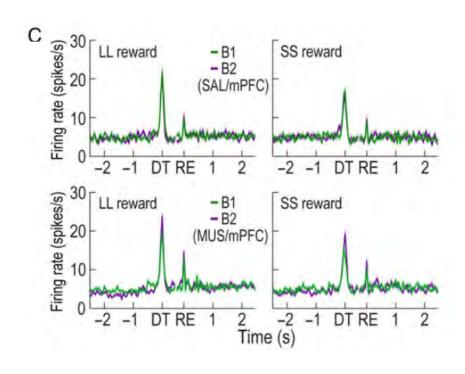
# mPFC inactivation > impairment of interval timing behavior

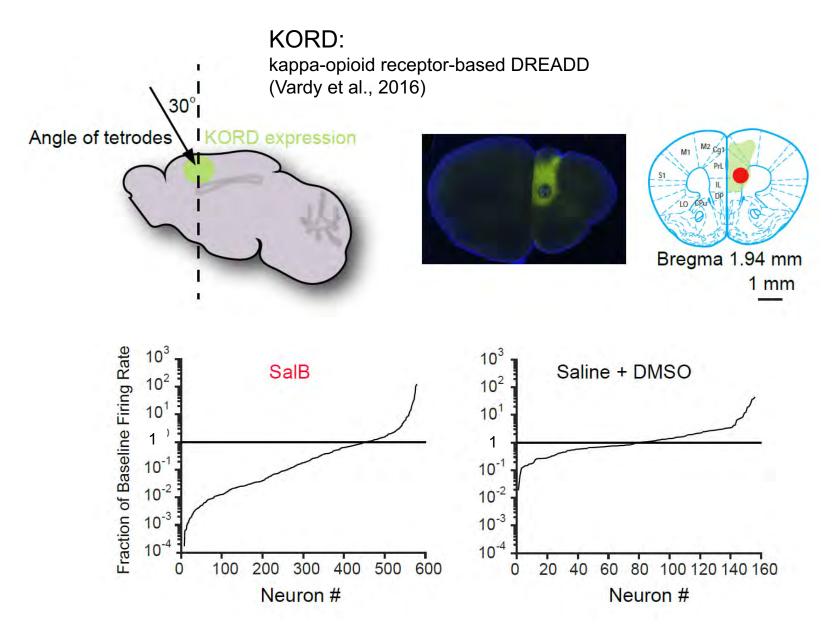




# mPFC inactivation → mild effect on dopamine RPEs



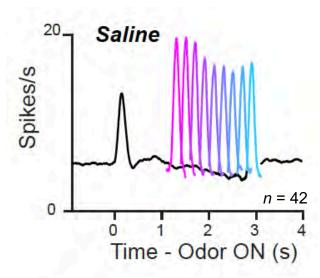


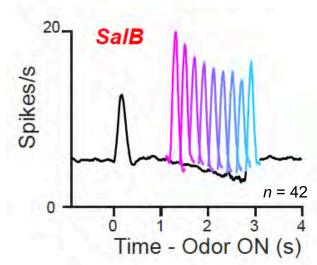


(Starkweather, Gerhsman, Uchida, unpublished)

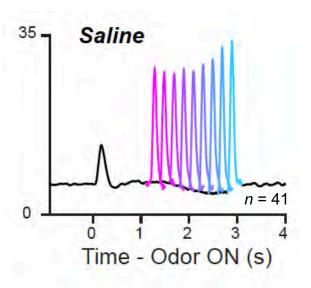
### mPFC inactivation

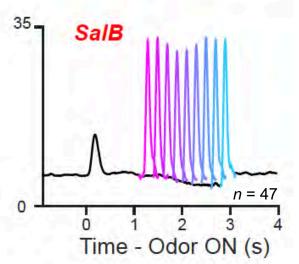
Task 1 (100% reward)





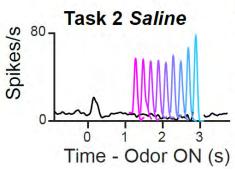
Task 2 (90% reward)

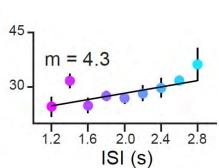


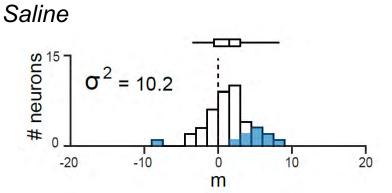


### Changes of individual neurons in Task 2

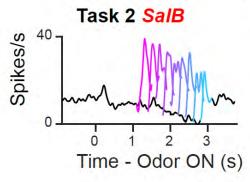
#### 1 example neuron:

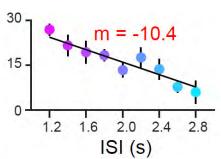


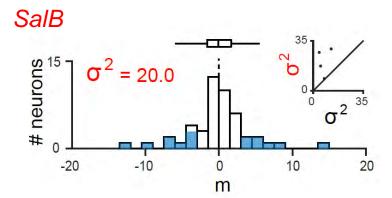




### 1 example neuron:

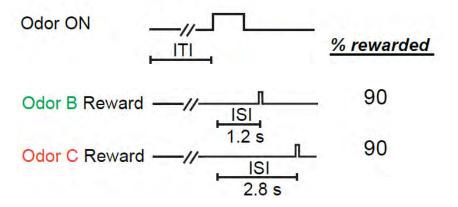




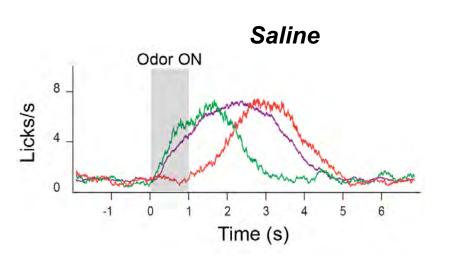


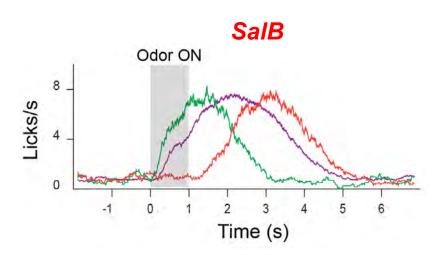
## mPFC inactivation does not affect the time course of anticipatory licking

Task 2: 90% Rewarded



\*Licking behavior on 10% reward omission trials

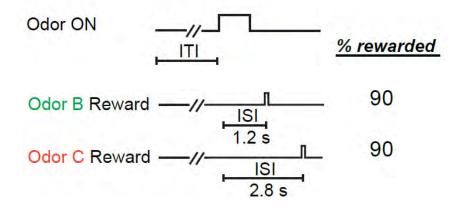


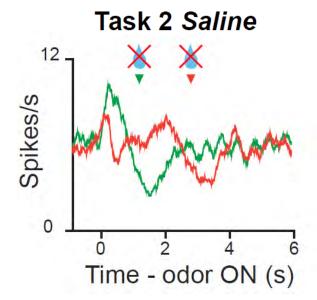


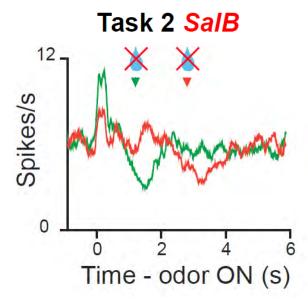
(Starkweather, Gerhsman, Uchida, unpublished)

# mPFC inactivation does not impair timing-related aspects of RPE

Task 2: 90% Rewarded







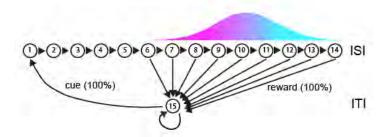
(Starkweather, Gerhsman, Uchida, unpublished)

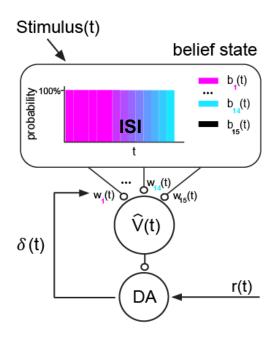
### Model-based predictions

What changes in the model recapitulate the observations?

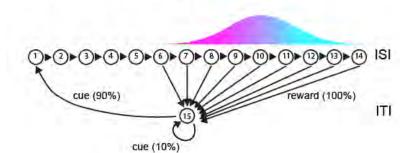
## Simulating specific impairments in the model

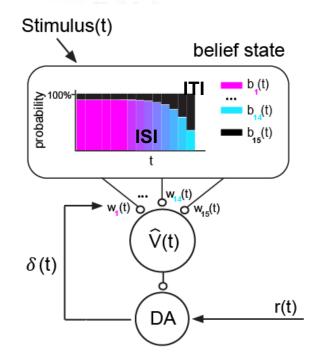
**Task 1** 100% Rewarded





**Task 2** 90% Rewarded

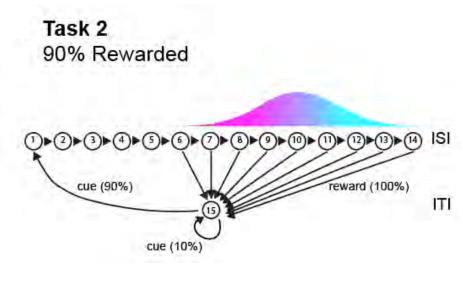


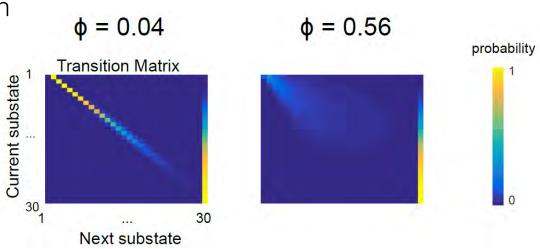


(Starkweather, Gerhsman, Uchida, unpublished)

## Modeling mPFC inactivation as a timing deficit

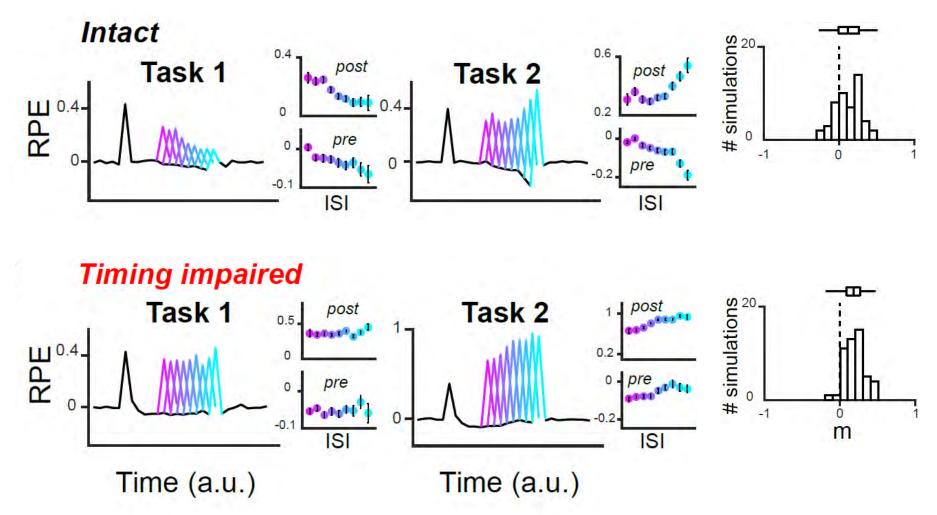
- Transition matrix stores knowledge of dwell time
  - Timing 'lesion' simulated by blurring transition matrix (Takahashi et al, 2016)
  - Ways to simulate timing deficit:
    - Increase Weber fraction



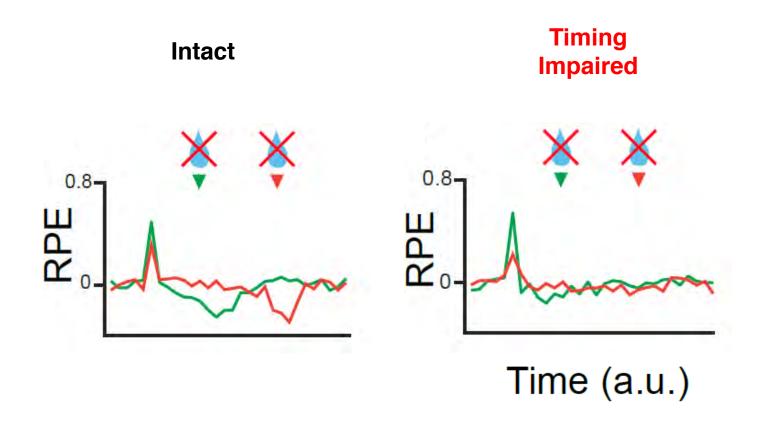


## Modeling mPFC inactivation as a timing deficit

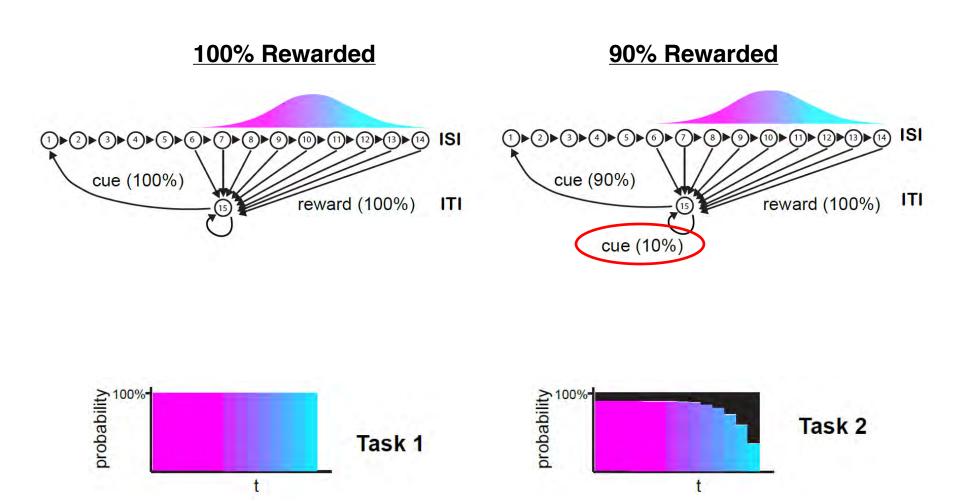
#### Model:



### Modeling mPFC inactivation as a timing deficit

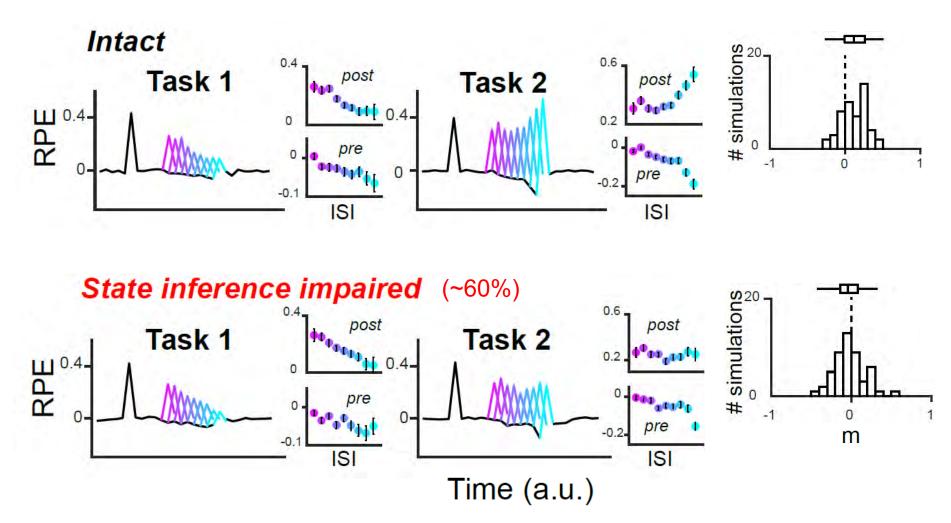


## Modeling mPFC inactivation: Hidden state inference deficit

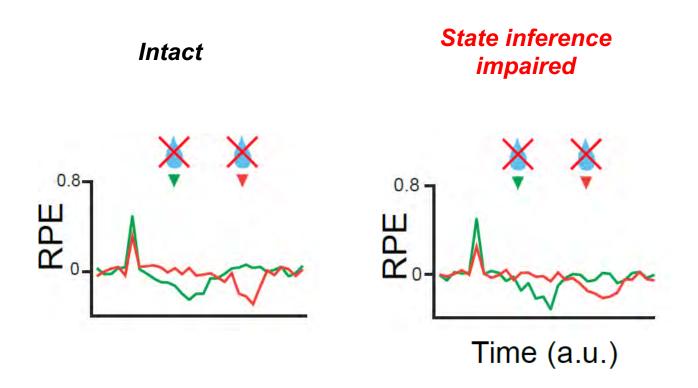


# Modeling mPFC inactivation as a hidden state inference deficit

#### Model:



## Modeling mPFC inactivation as a hidden state inference deficit



# Summary

- Dopamine RPEs are shaped by
  - Interval timing (hazard rate)
  - Hidden state inference (belief state)

 A TD model in which reward expectation is computed over belief states uniquely explains dopamine responses.

 Processes of interval timing and hidden state inference can be separated experimentally.

## Dopamine RPE and inference

J Neurophysiol 104: 1068-1076, 2010.

First published June 10, 2010; doi:10.1152/jn.00158.2010.

#### A Pallidus-Habenula-Dopamine Pathway Signals Inferred Stimulus Values

Ethan S. Bromberg-Martin, Masayuki Matsumoto, 1,2 Simon Hong, and Okihide Hikosaka 1

<sup>1</sup>Laboratory of Sensorimotor Research, National Eye Institute, National Institutes of Health, Bethesda, Maryland; and <sup>2</sup>Primate Research Institute, Kyoto University, Inuyama, Aichi, Japan





#### Temporal Specificity of Reward Prediction Errors Signaled by Putative Dopamine Neurons in Rat VTA Depends on Ventral Striatum

Yuji K. Takahashi, 1,5,\* Angela J. Langdon, 2,5 Yael Niv, 2 and Geoffrey Schoenbaum 1,3,4,\*

Article



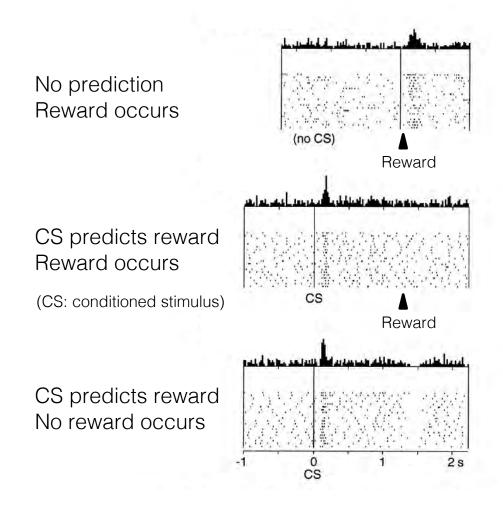
#### Midbrain Dopamine Neurons Signal Belief in Choice Accuracy during a Perceptual Decision

Armin Lak, 1,2 Kensaku Nomoto, 3,4 Mehdi Keramati, 5 Masamichi Sakagami, 3 and Adam Kepecs 1,6,\*

## Topics

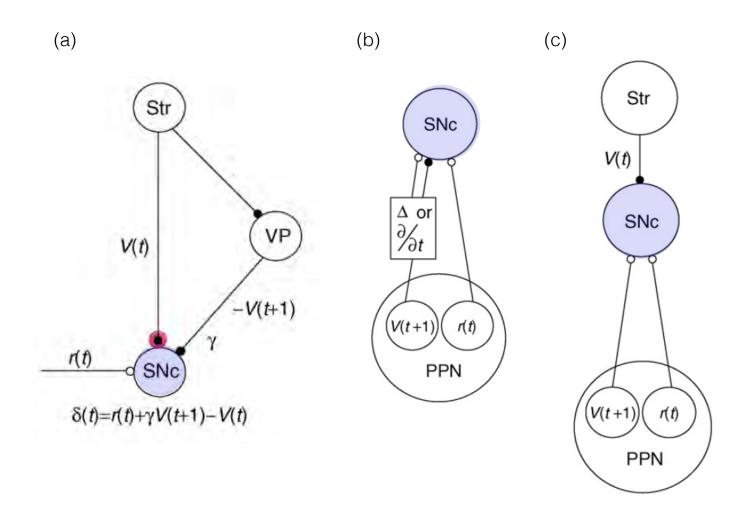
- A mouse model to study dopamine RPE
- Do all dopamine neurons signal RPEs?
- What is the "state" in reinforcement learning?
- How are RPEs computed?
- Diversity of dopamine neurons

# Firing of putative dopamine neurons

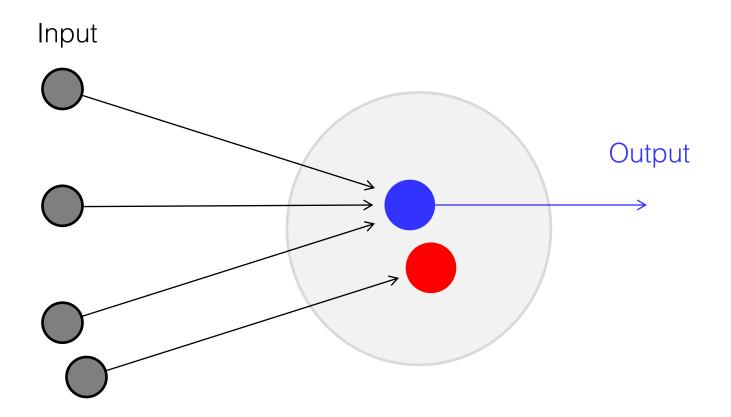


$$\delta(t) = r(t) + \gamma \hat{V}(t+1) - \hat{V}(t)$$

#### Models of RPE computation

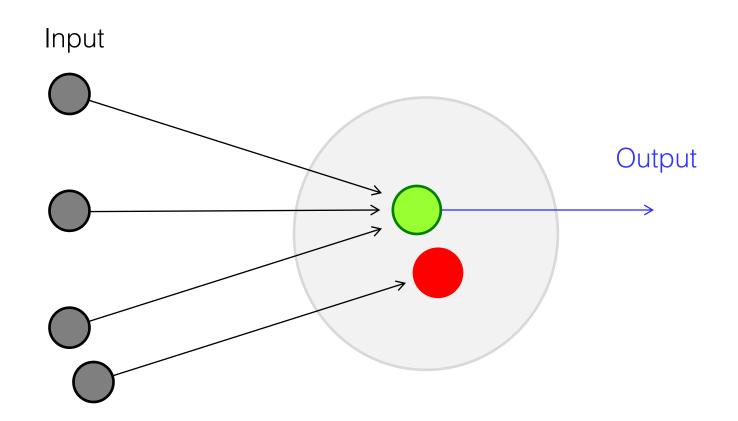


#### Where do other inputs come from?

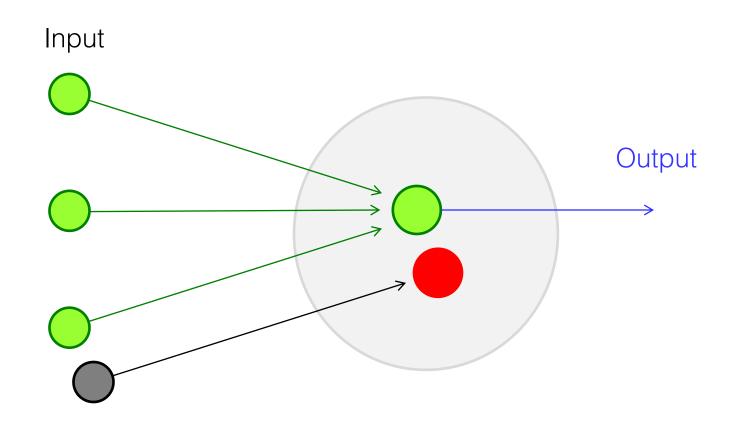


Conventional tracers are taken up non-specifically...

# Where do other inputs come from?



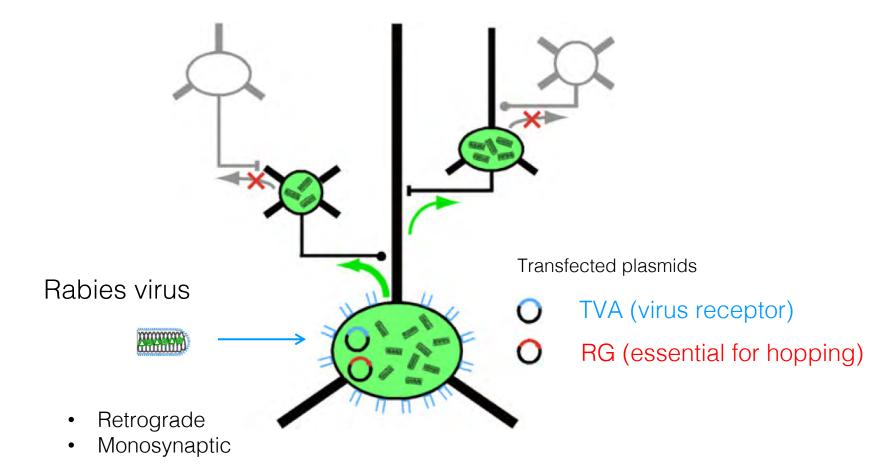
# Where do other inputs come from?



#### Monosynaptic Restriction of Transsynaptic Tracing from Single, Genetically Targeted Neurons

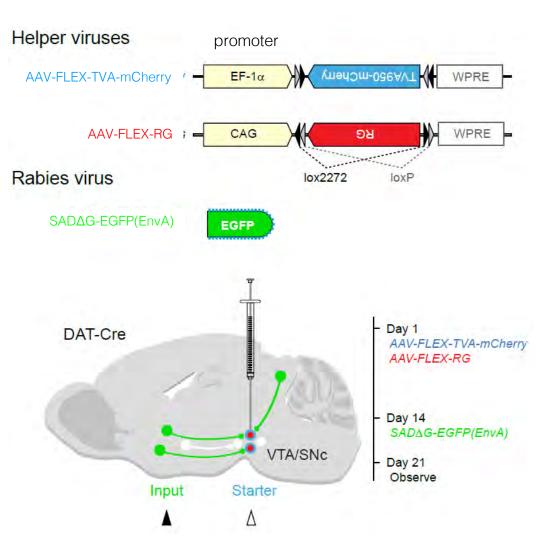
Ian R. Wickersham,<sup>1,\*</sup> David C. Lyon,<sup>1,4</sup> Richard J.O. Barnard,<sup>2,5</sup> Takuma Mori,<sup>1</sup> Stefan Finke,<sup>3,6</sup> Karl-Klaus Conzelmann,<sup>3</sup> John A.T. Young,<sup>2</sup> and Edward M. Callaway<sup>1</sup>

Rabies virus-mediated monosynaptic input tracing



## Rabies virus-mediated input tracing

AAV: adeno-associated virus



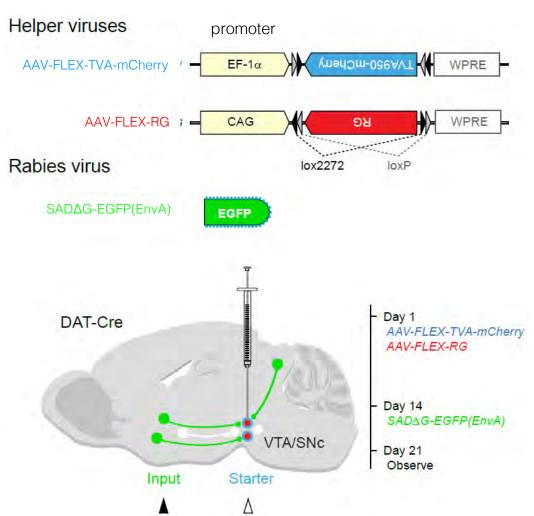
TVA: Virus receptor

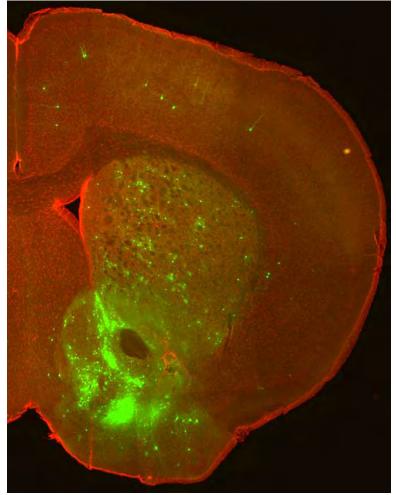
RG (Rabies glycoprotein): essential for transsynaptic hopping

Miyamichi et al. 2010 Haubensak et al. 2010 Wall et al. 2010

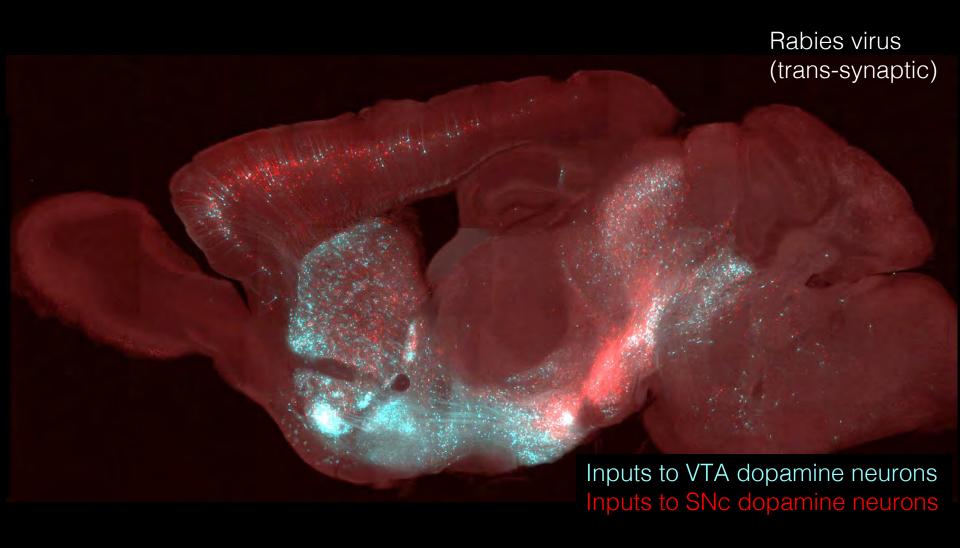
# Rabies virus-mediated input tracing

AAV: adeno-associated virus



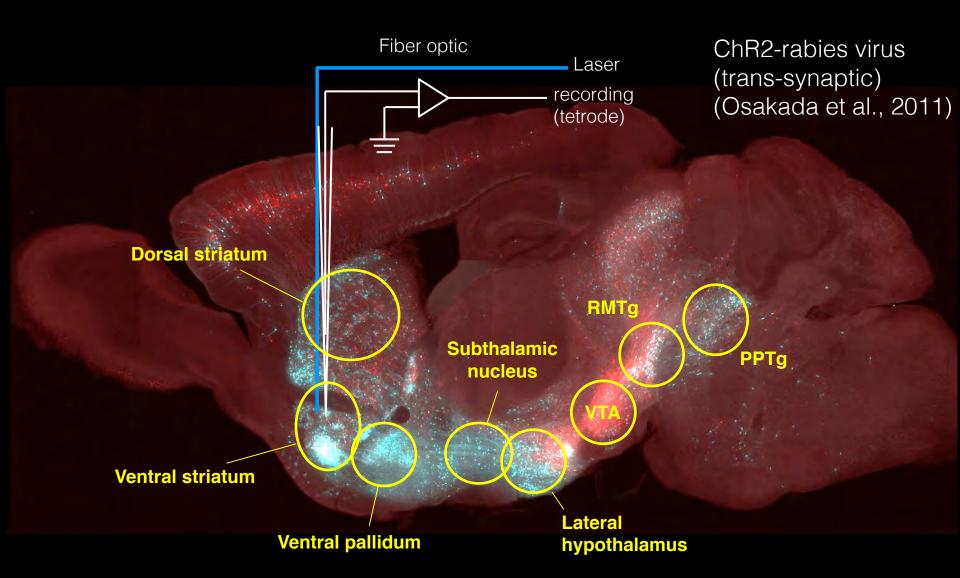


## Direct inputs to dopamine neurons



(Watabe-Uchida et al., Neuron, 2012)

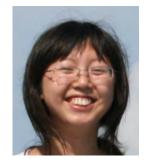
#### Recording from direct inputs of dopamine neurons



(Tian et al., Neuron, 2016)

PPTg: pedunculopontine nucleus RMTg: rostromedial tegmental area

### Recording from direct inputs to dopamine neurons







Mitsuko Watabe-Uchida



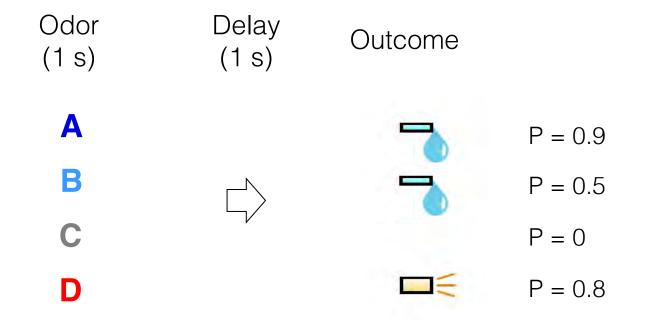
99 mice



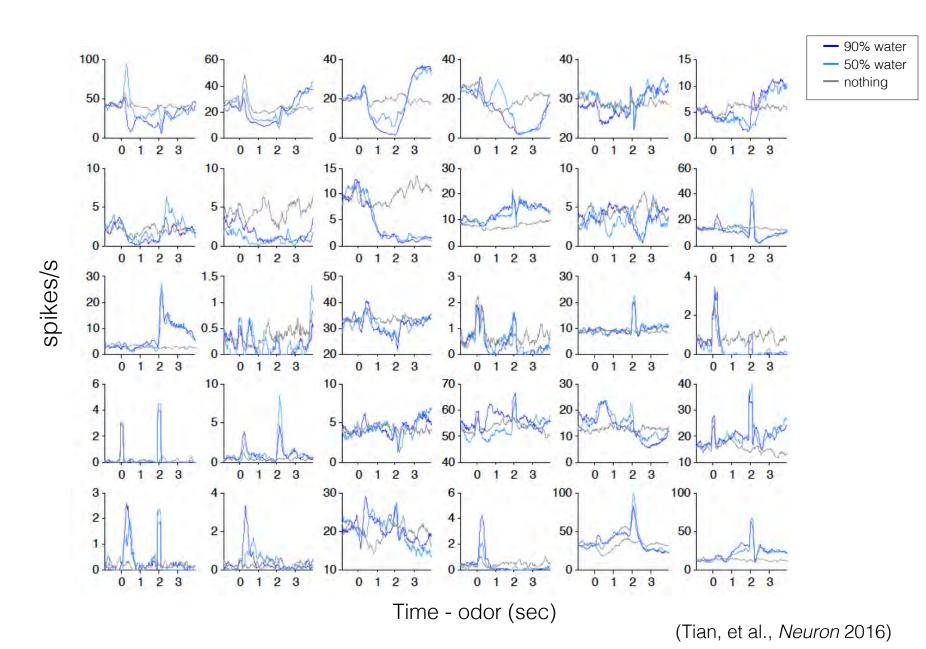
1,931 neurons from 7 input areas



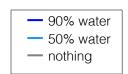
205 identified input neurons

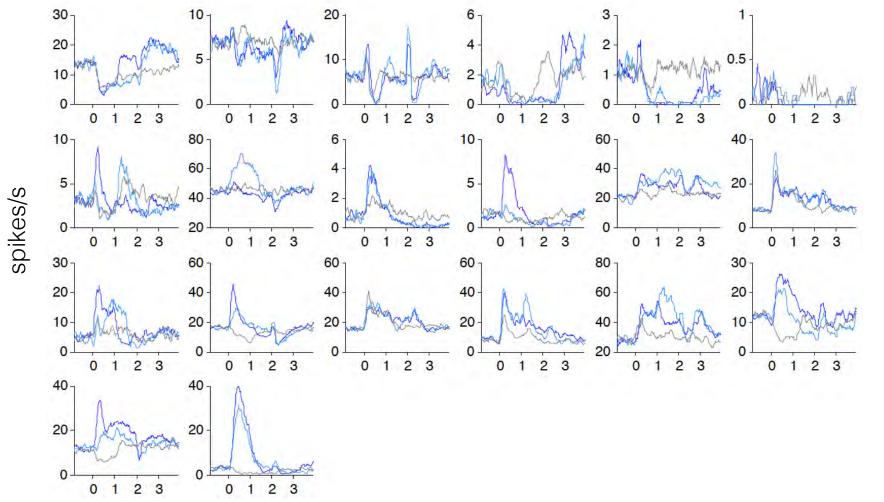


#### Activity of input neurons (Pedunculopontine tegmental area)



#### Activity of input neurons (Ventral striatum)

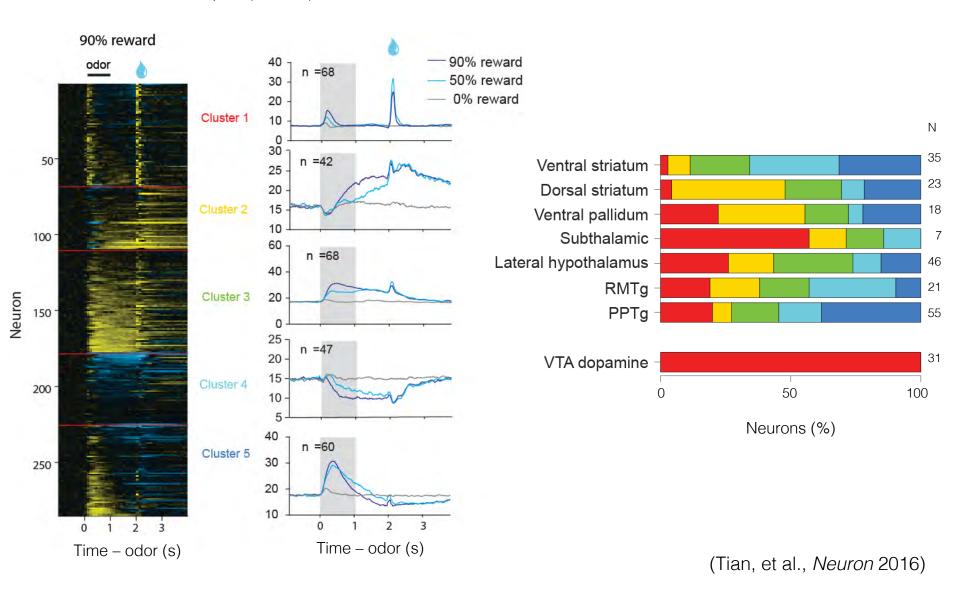




Time - odor (sec)

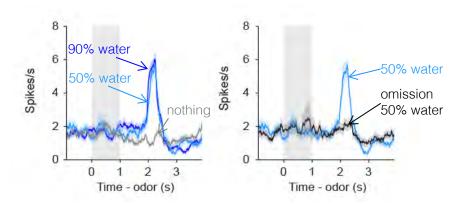
#### Diverse firing patterns of identified input neurons

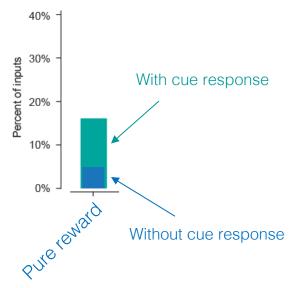
All identified inputs (n = 205) and VTA neurons



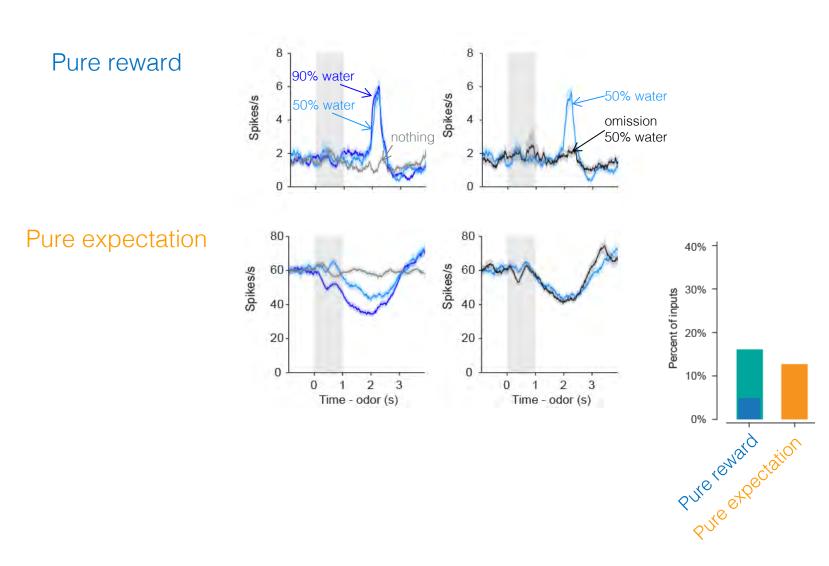
# Pure reward coding neurons?

#### Pure reward



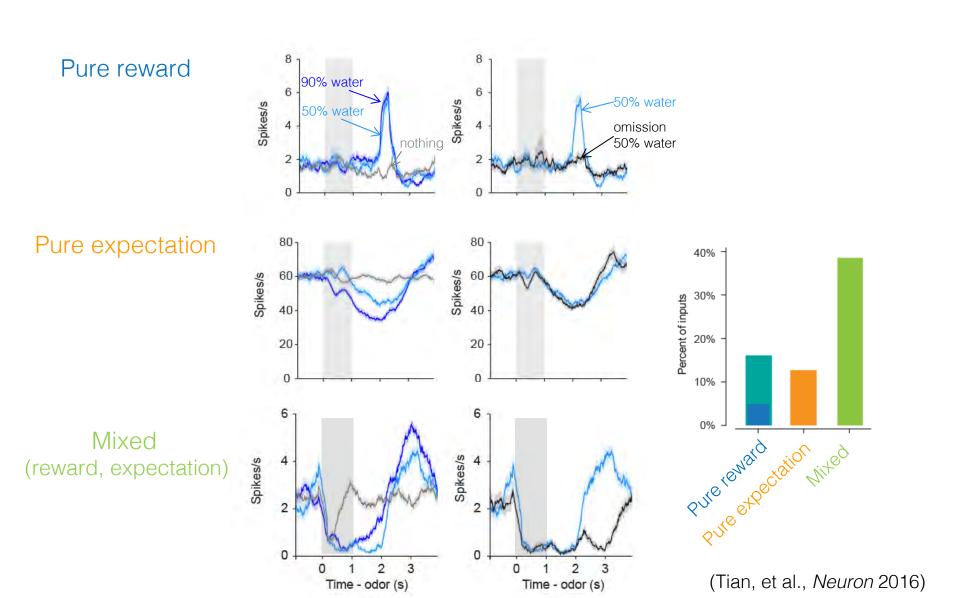


# Pure expectation coding neurons?

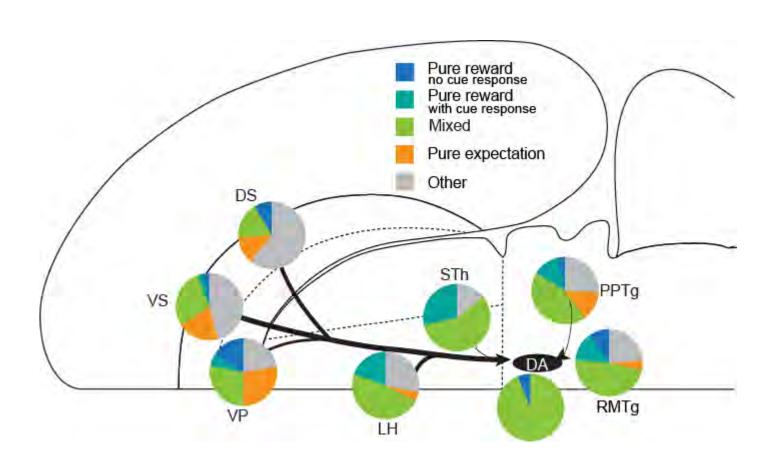


(Tian, et al., Neuron 2016)

#### Many input neurons encode both reward and expectation

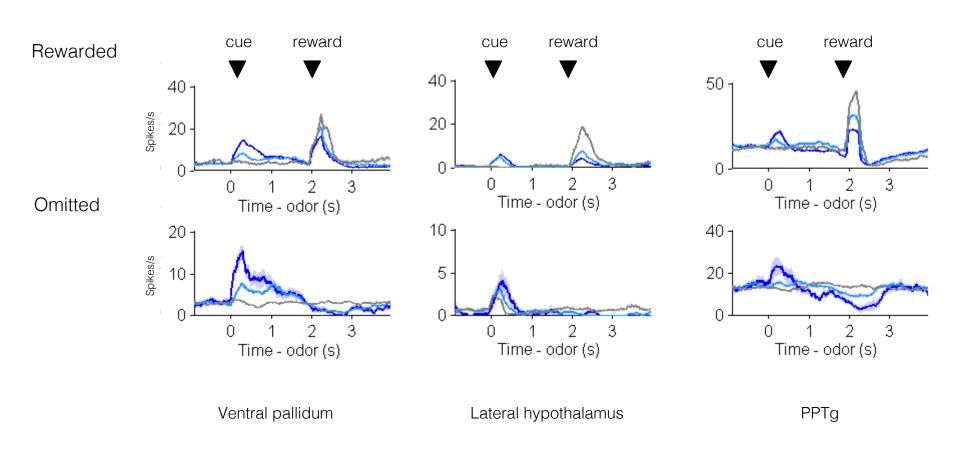


# Mixed coding of reward and expectation signals in identified input neurons

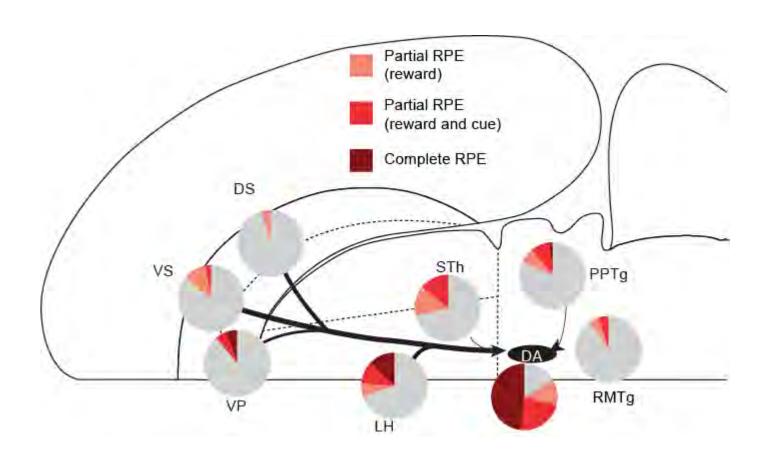


#### Some input neurons already have RPE signals

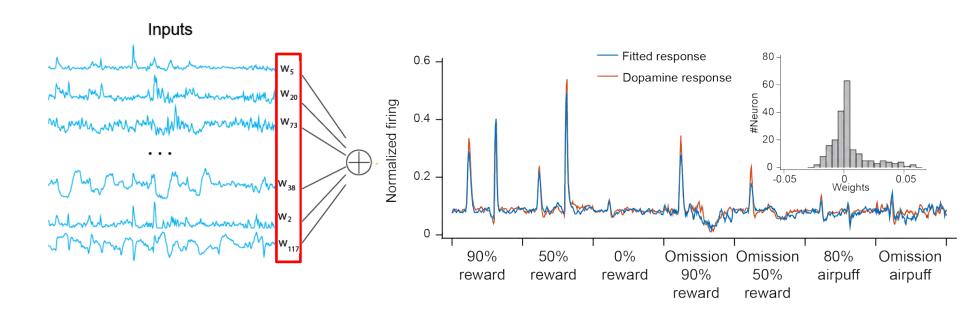




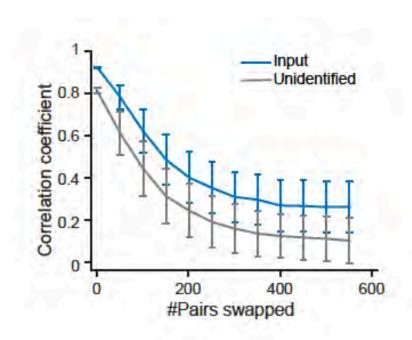
## Identified input neurons encode RPE signals



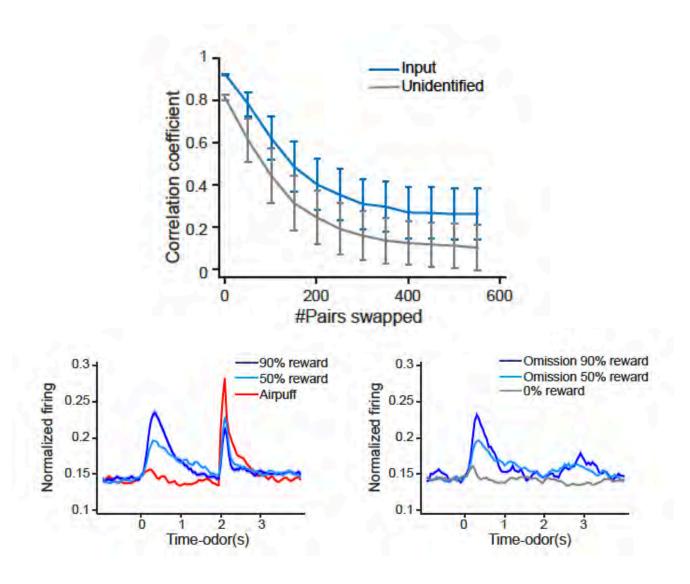
# Precise weights of inputs are not required for reading out of RPE signals



# RPE-like responses without fine tuning



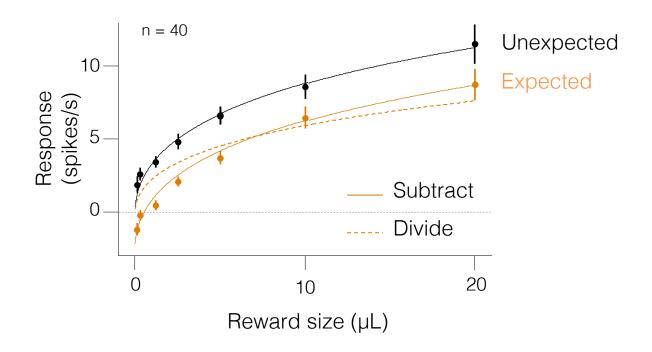
## RPE-like responses without fine tuning



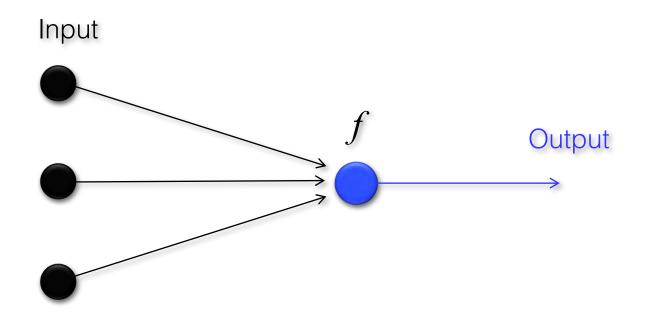
#### Activity of input neurons (summary)

- All tested areas contain neurons with diverse firing patterns.
- Most neurons do not encode a single variable. Information about reward and expectation are already combined in a complex manner.
- RPEs are already partially computed in some input neurons.
- Despite these complexities at the level of inputs, once they are combined, dopamine neurons signal RPEs in an extremely homogeneous fashion.
- Random combinations of inputs can recapitulate aspects of RPEs except for some specific components such as their response during air puff or reward omission.

## Reward expectation triggers subtraction



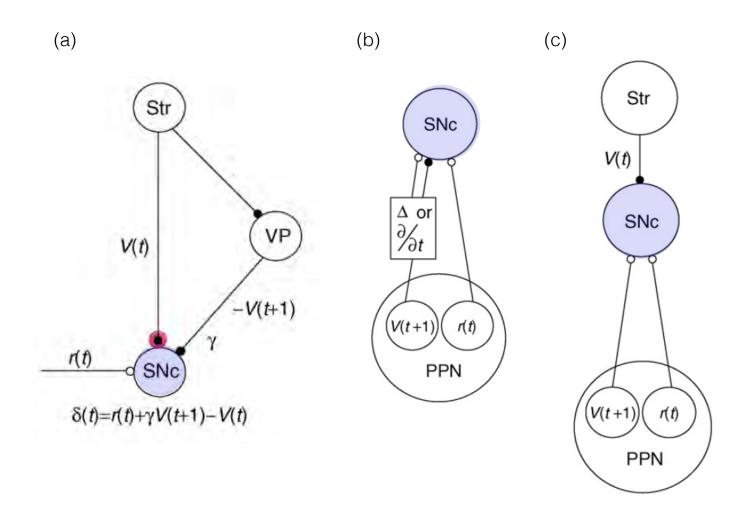
## Understanding computation (arithmetic) in the brain



$$\delta = V_{actual} - V_{expected}$$

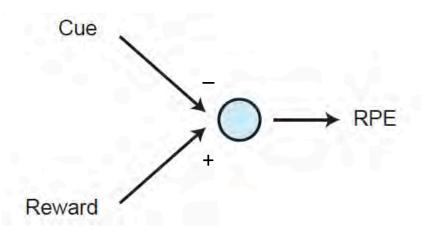
$$\delta = r + V(t) - V(t-1)$$

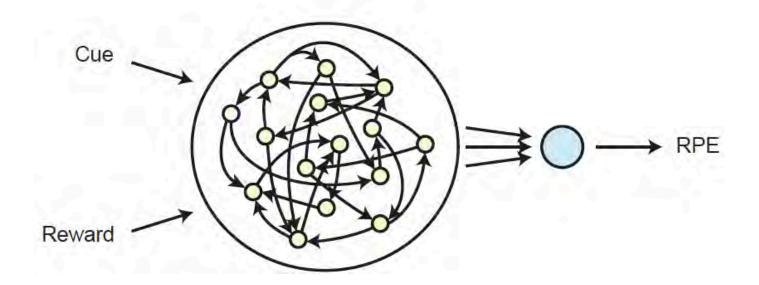
#### Models of RPE computation



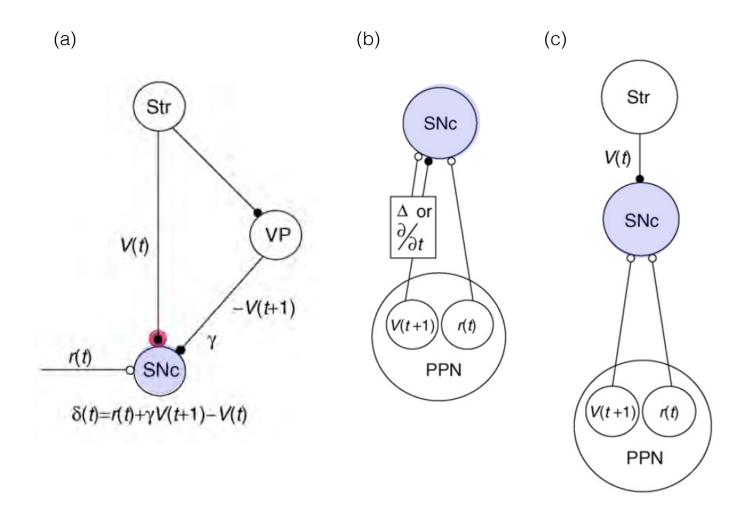
#### Arithmetic in the brain

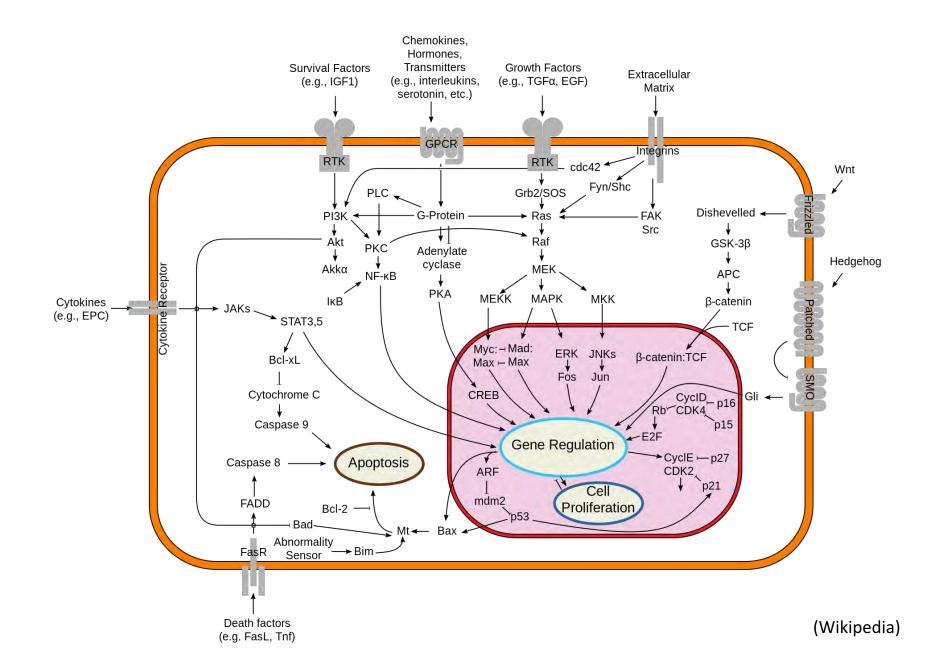
- Representation might not be simple (pure)
- Computation might be distributed and/or gradual
  - Mixing information ("mixed selectivity") in non-linear way may expand the space of information coding and/or facilitate the readout of downstream neurons (Fusi et al., 2016).
  - Representation and computation may be embedded in patterns of population activities (Rigotti et al. 2013; Mante et al., 2013; etc.)
- Computing with recurrent network and loop. Theory??



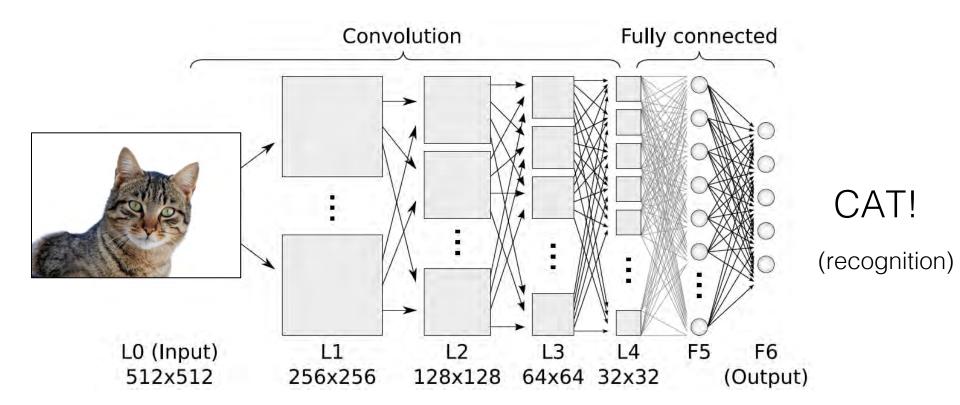


#### Models of RPE computation





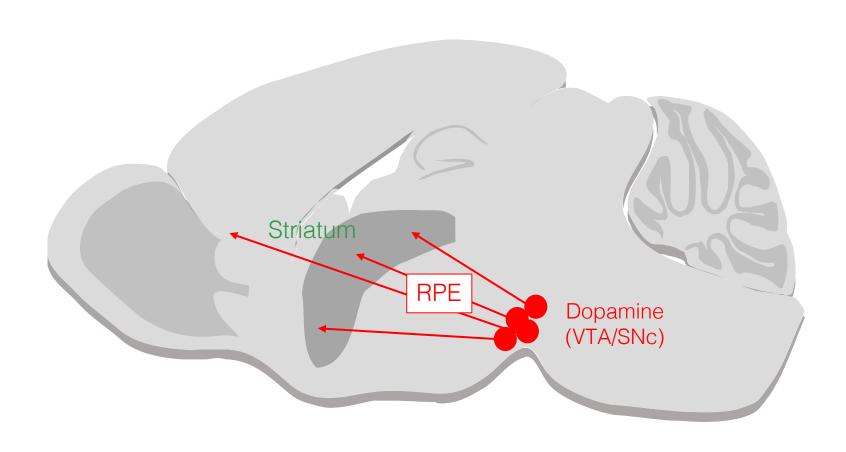
#### Deep learning



## Topics

- A mouse model to study dopamine RPE
- Do all dopamine neurons signal RPEs?
- What is the "state" in reinforcement learning?
- How are RPEs computed?
- Diversity of dopamine neurons

#### Dopamine neurons broadcast reward prediction error (RPE)

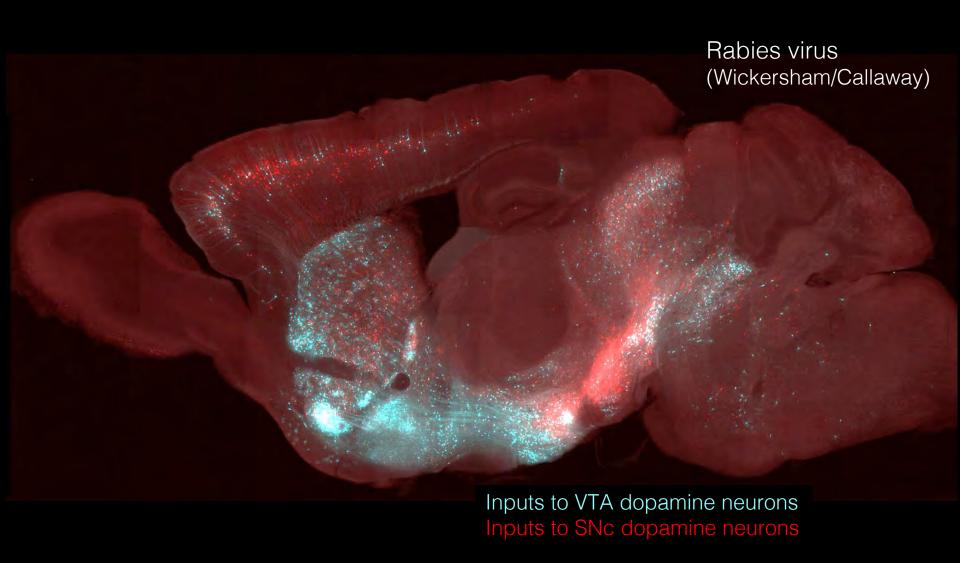


# Do all dopamine neurons signal RPEs?

Diversity of dopamine neurons

- Anatomy (inputs)
- Dopamine signals (fiber fluorometry)

# Direct inputs to dopamine neurons



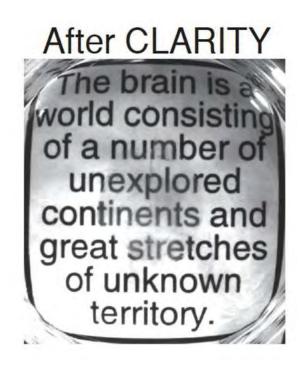
(Watabe-Uchida et al., Neuron, 2012)

# Toward large-scale mapping

- CLARITY (brain-clearing method)
- Light-sheet imaging
- Automated analysis
  - Registering each brain to a standard brain (atlas)
  - Cell counting

# CLARITY: a brain-clearing method

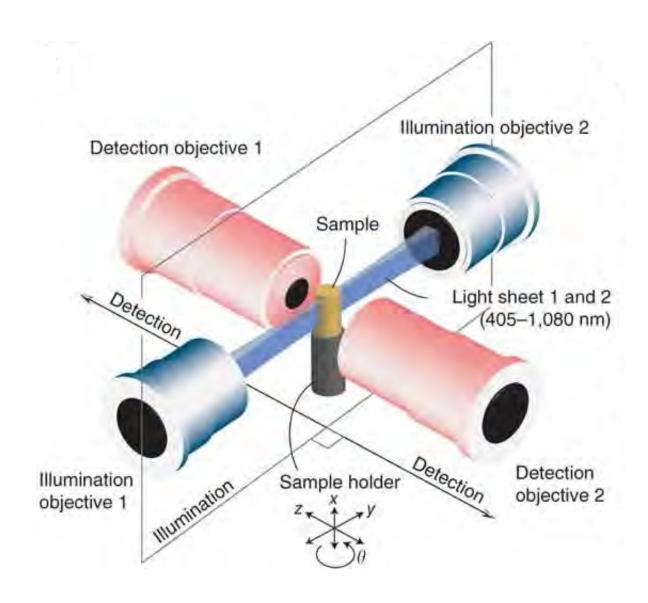
# The brain is a world consisting of a reper of une ed continued and great suches of unknown territory.



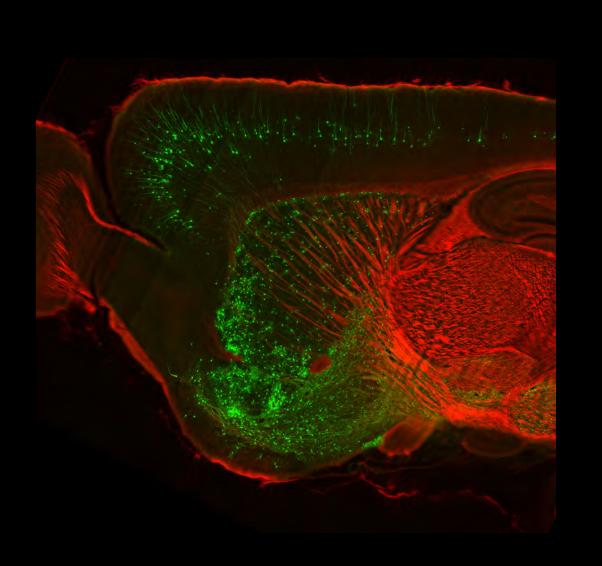
# CLARITY: a brain-clearing method

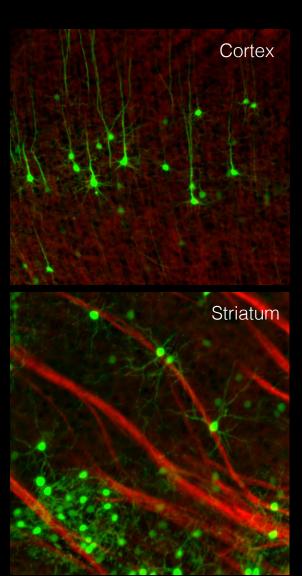
Step 1: hydrogel monomer infusion (days 1-3) 4°C Vesicle NHCH, NHCOC=C Plasma membrane Step 2: hydrogel-tissue hybridization (day 3) 37 °C NHCH,NH Hydrogel Step 3: electrophoretic tissue clearing (days 5-9) Extracted lipids in SDS micelle SDS micelle  $\Theta$ 

# Light-sheet microscopy

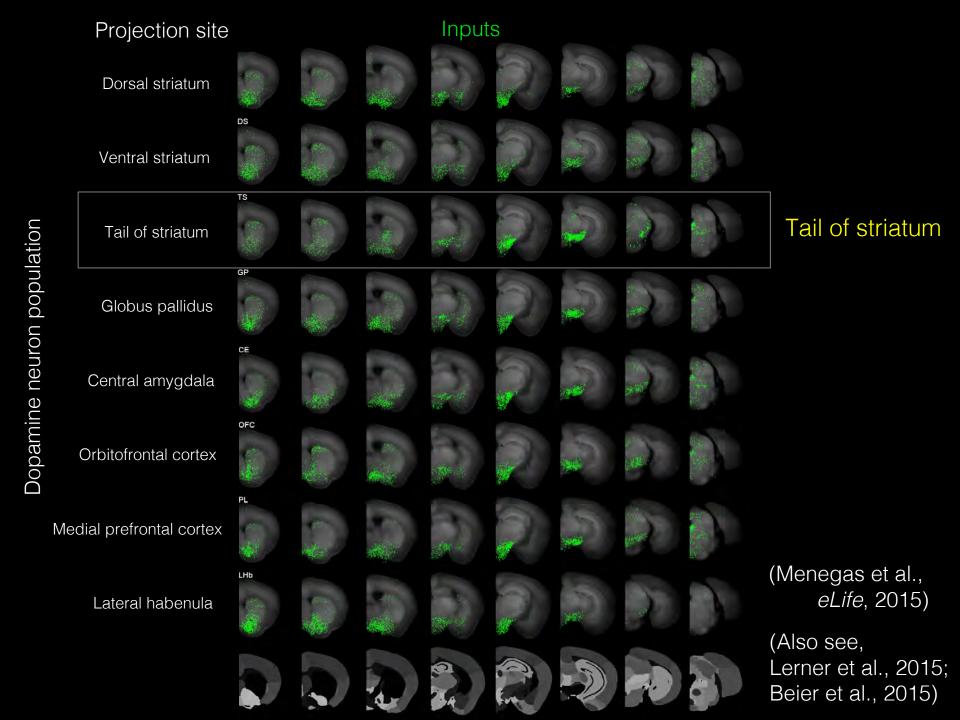


# CLARITY + Light-sheet imaging





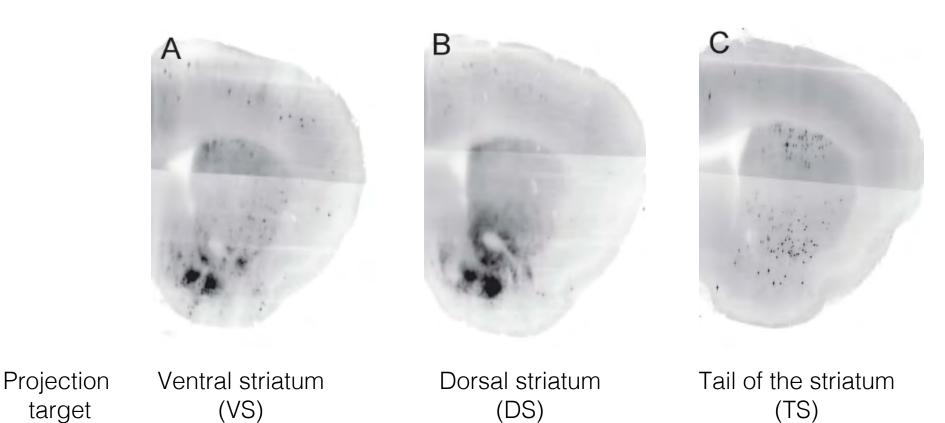
(Menegas et al., eLife, 2015)



#### Unique input pattern for TS dopamine

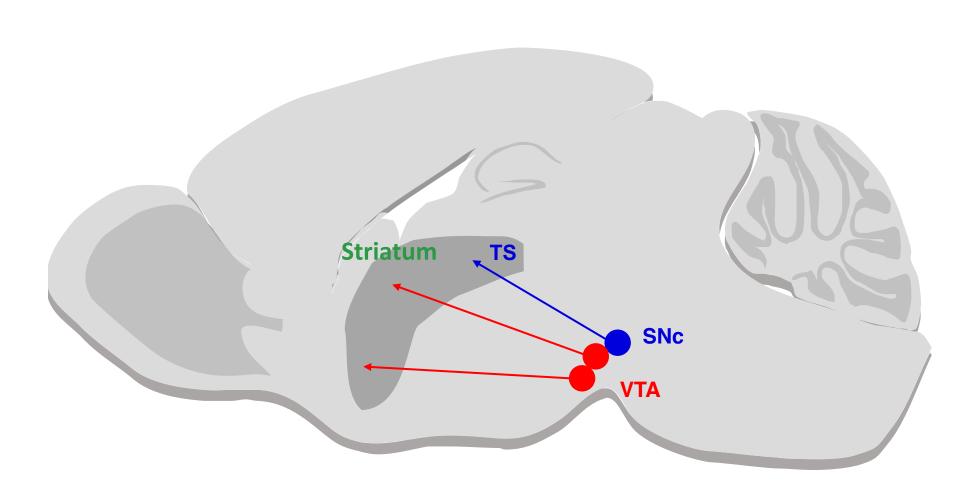
Inputs to dopamine neurons

target



(Menegas et al., eLife, 2015)

# TS dopamine: anatomically unique population



# Controversy

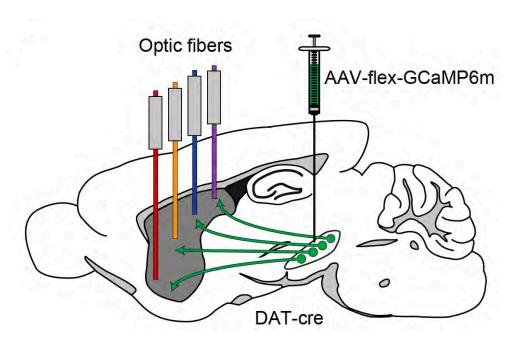
#### Do all dopamine neurons signal reward prediction errors?

- Aversive stimuli
- Some dopamine neurons are activated by aversive stimuli (Matsumoto & Hikosaka, 2009; Lerner et al., 2015)

- Novel stimuli
- Potential reward or novelty itself is rewarding
- Positive value of exploration (Kakade & Dayan, 2002; Horvitz et al., 1997)

#### Calcium imaging at dopamine projection targets

#### Fiber fluorometry (photometry)



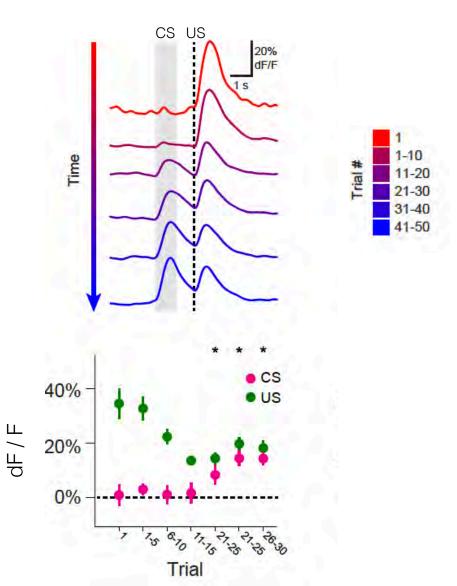
Kudo et al. (1992) Davis and Schmidt (2000) Adelsberger et al. (2005) Murayama et al. (2007)

Cui et al. (2013) Gunaydin et al. (2014) Lerner et al. (2015) Parker et al. (2016) Howe and Dombeck (2016)

- Calcium indicator (GCaMP6m) in dopamine neurons
- Head-fixed mice
- Classical conditioning (reward, air puff, neutral stimuli)

# Ventral striatum (VS) dopamine signals RPE

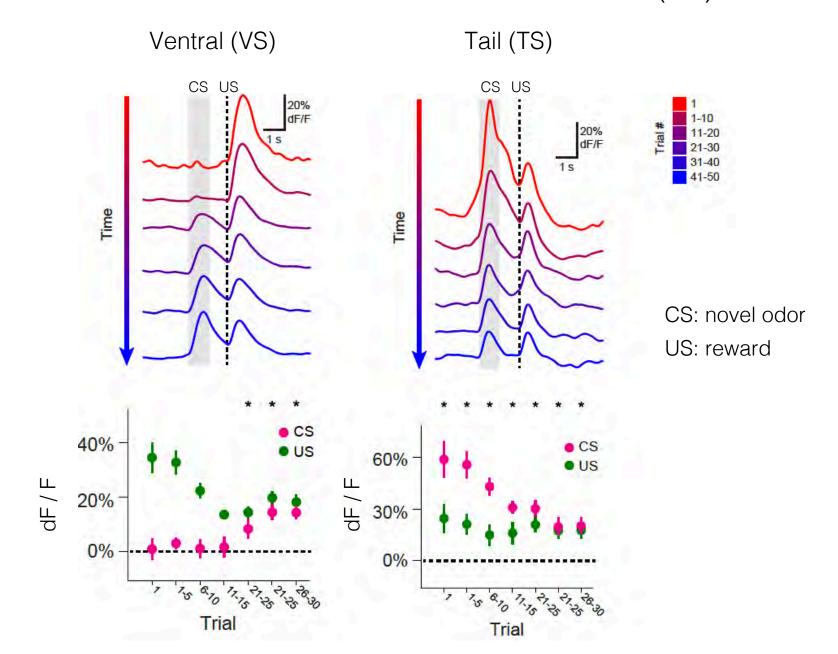




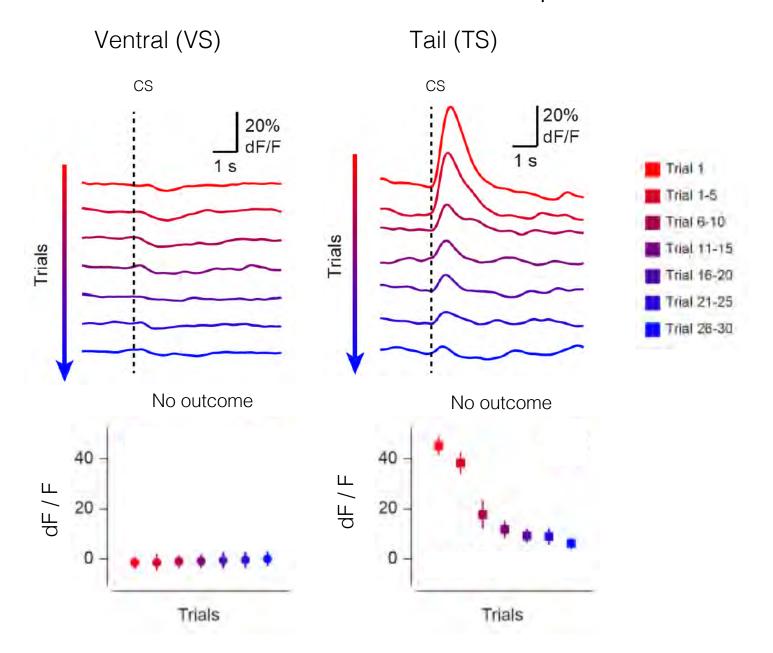
CS: novel odor

US: reward

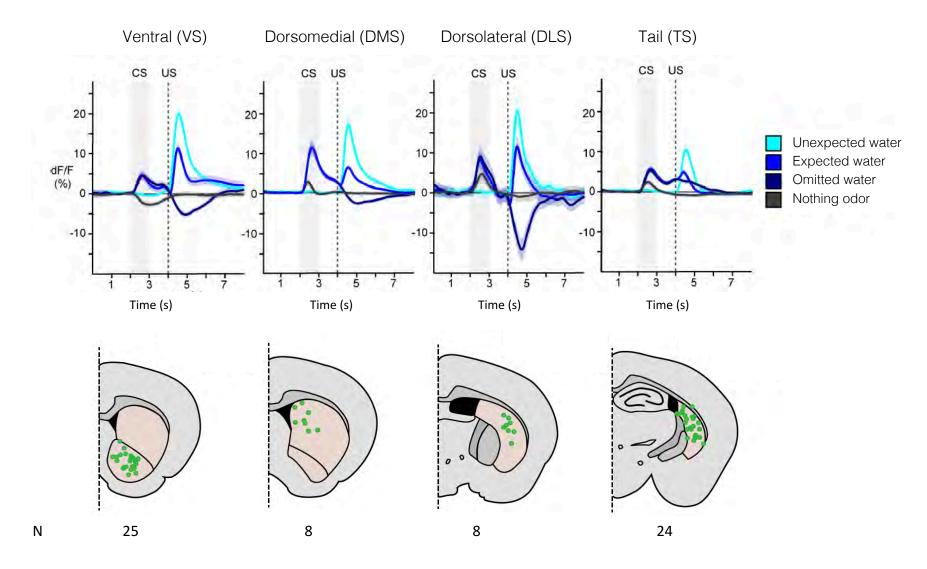
#### **Novel stimuli** activate the tail of the striatum (TS)



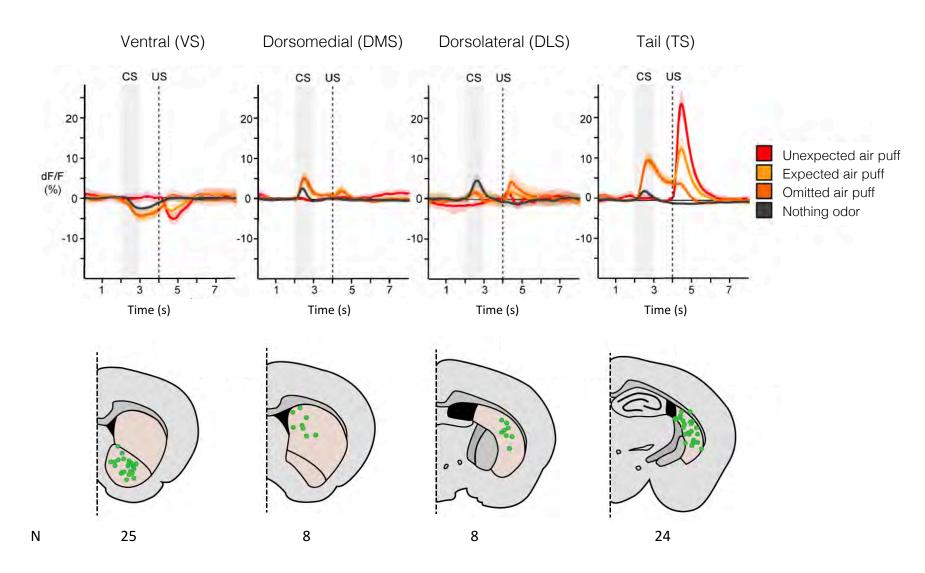
#### Novel stimuli activate TS but not VS dopamine



#### Responses to **reward** are relatively similar across areas

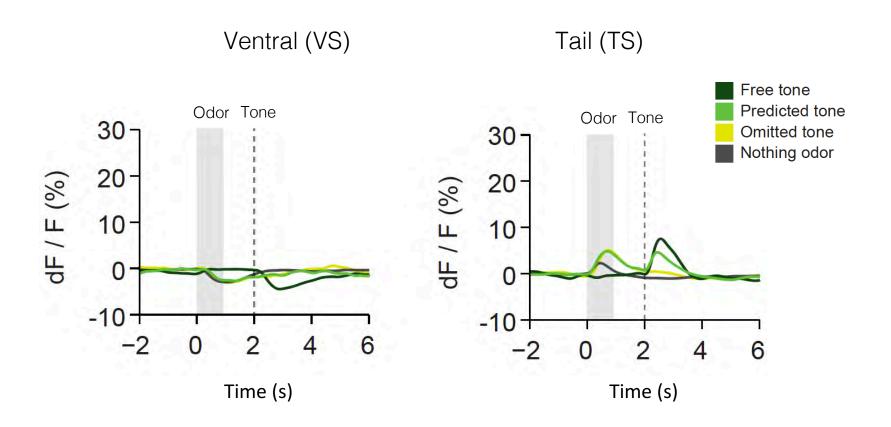


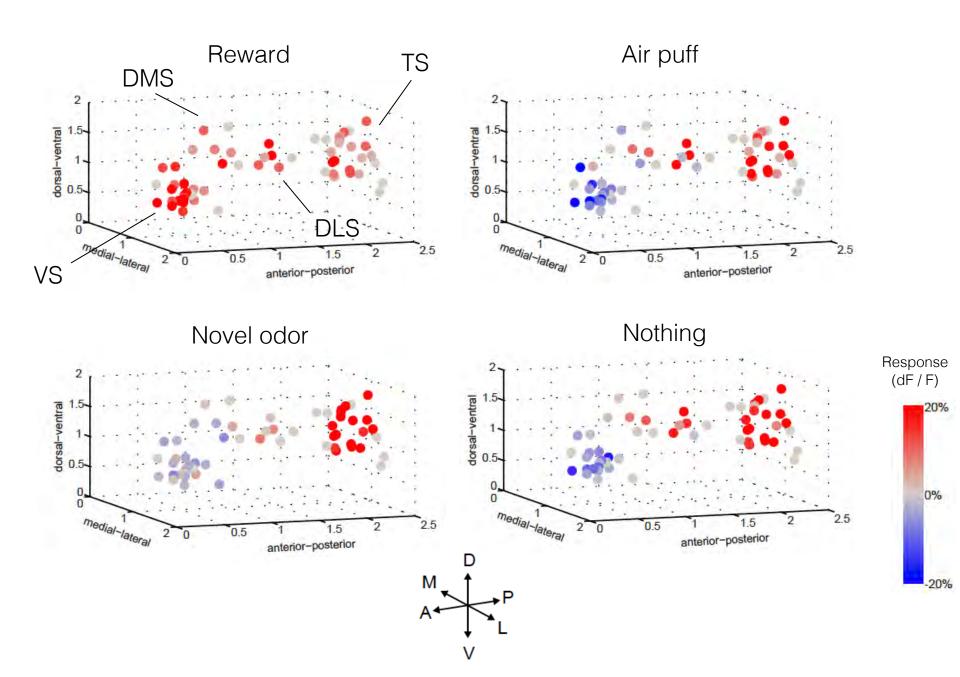
#### Responses to air puff are distinct among striatal areas



#### Mild tones activate TS but not VS dopamine

~ 55 dB



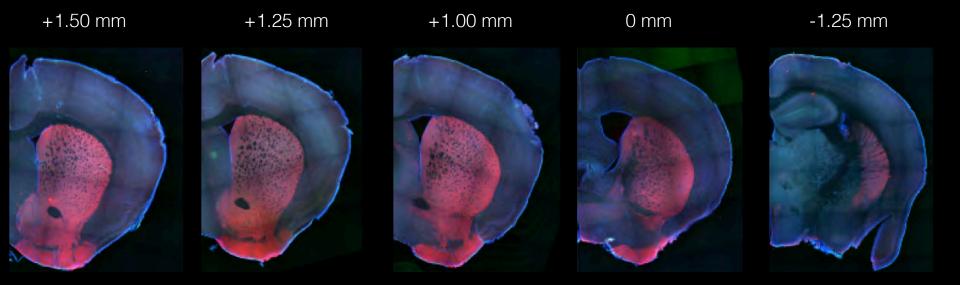


#### Conclusion

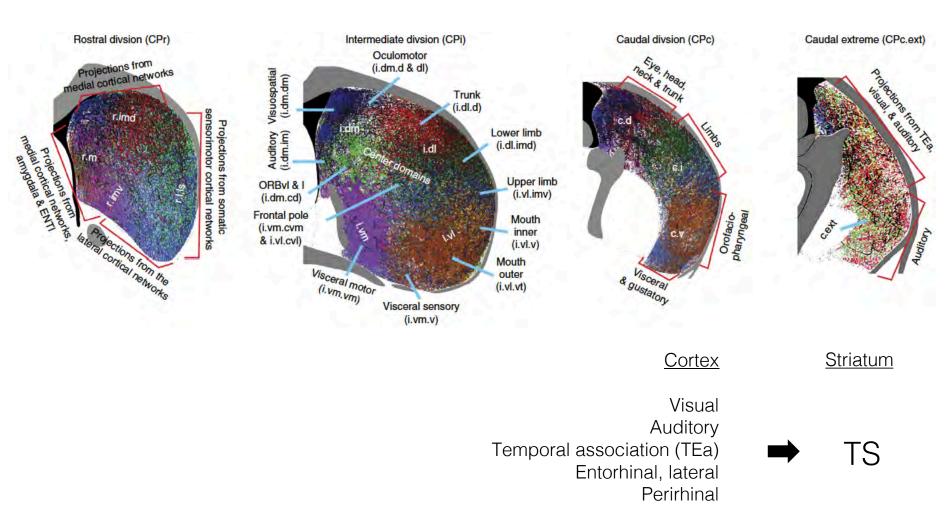
 Dopamine neurons projecting to the ventral striatum (VS) signal canonical value prediction errors.

(Schultz, Glimcher, Phillips, Roitman, Cheer etc.)

- Dopamine neurons projecting to the tail of the striatum (TS) form a distinct population both anatomically and functionally.
- TS dopamine is activated by salient stimuli (cf. lateral SNc: Matsumoto & Hikosaka, 2009)
- Novel stimuli activate TS but not VS dopamine
- Dopamine neurons' responses to novel stimuli can be understood as a part of general salience signal in TS but unlikely to be a positive value of exploration ("novelty bonus").



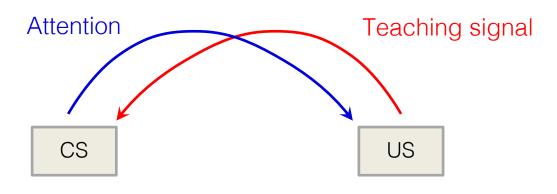
# The tail of the striatum (TS) receives inputs from sensory cortices



(Hintiryan et al., 2016; also see Hunnicutt et al. 2016)

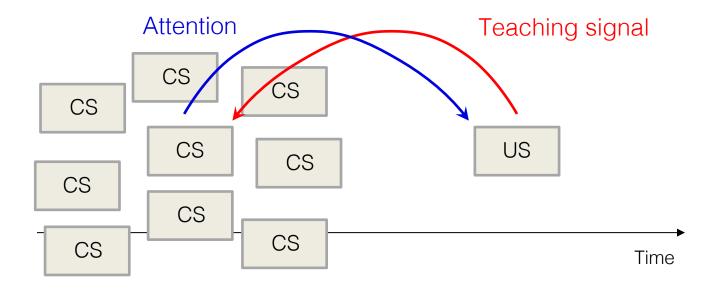
- Associability (the effectiveness of associative learning)
  - **US associability**  $\propto$  *US unpredictability*

- CS associability  $\propto$  CS unpredictability or US unpredictability



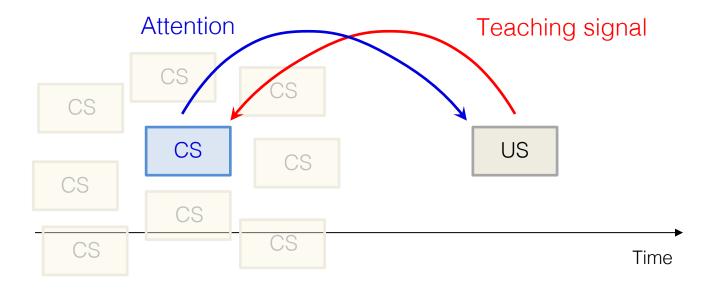
- Associability (the effectiveness of associative learning)

- CS associability  $\propto$  CS unpredictability or US unpredictability



- Associability (the effectiveness of associative learning)
  - **US associability**  $\propto$  *US unpredictability*

- CS associability  $\propto$  CS unpredictability or US unpredictability



- Associability (the effectiveness of associative learning)
  - US associability  $\propto US$  unpredictability

- CS associability  $\propto$  CS unpredictability or US unpredictability

- VS dopamine: US associability (reward prediction error)
- TS dopamine: CS associability (attention)
- TS attention system may help select behaviorally-relevant stimuli to increase the efficiency of reinforcement learning.

# Distinct dopamine signals in striatal regions

- Ventral striatum
  - Value prediction error (VPE)
- Dorsal striatum (dorsomedial and dorsolateral)
  - Mixture of VPE, salience and motion\*(?)
- Tail of the striatum
  - General salience (attention)
    - Attention for associative learning (CS associability?)

\*cf. Jin and Costa (2010)

Howe and Dombeck (2016)

Parker et al. (2016)

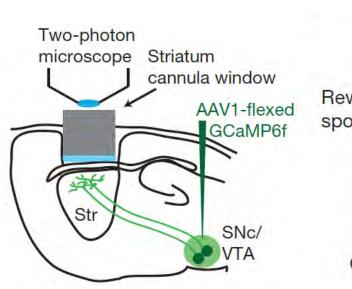
Barter et al. (2015)

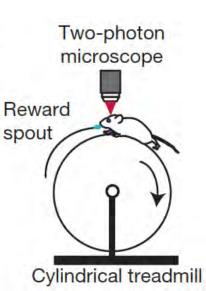
Also see, Lerner et al. (2015)

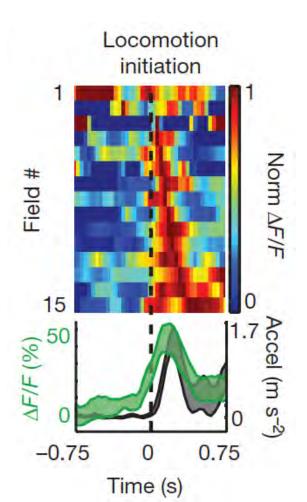


# Rapid signalling in distinct dopaminergic axons during locomotion and reward

M. W. Howe1 & D. A. Dombeck1







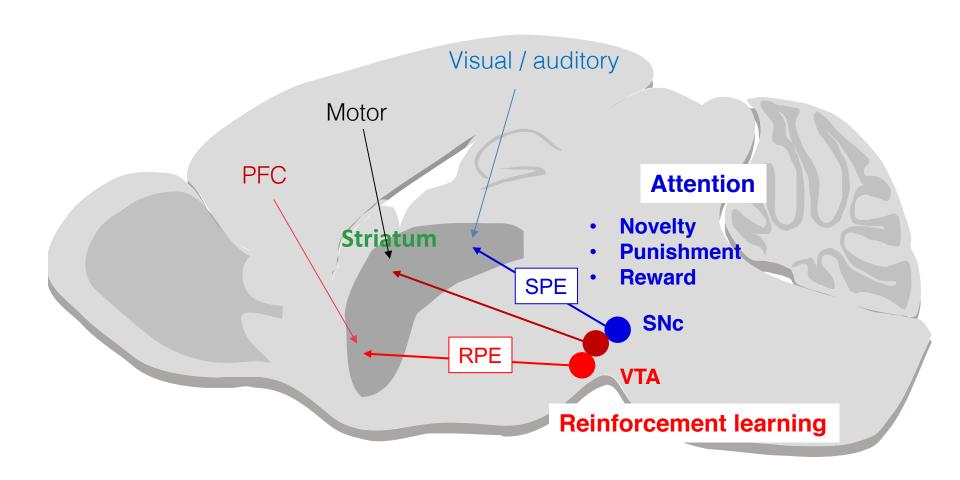
# Dopamine as a TD error

- Supporting evidence
- Minor problems
- Serious problems

# Future questions

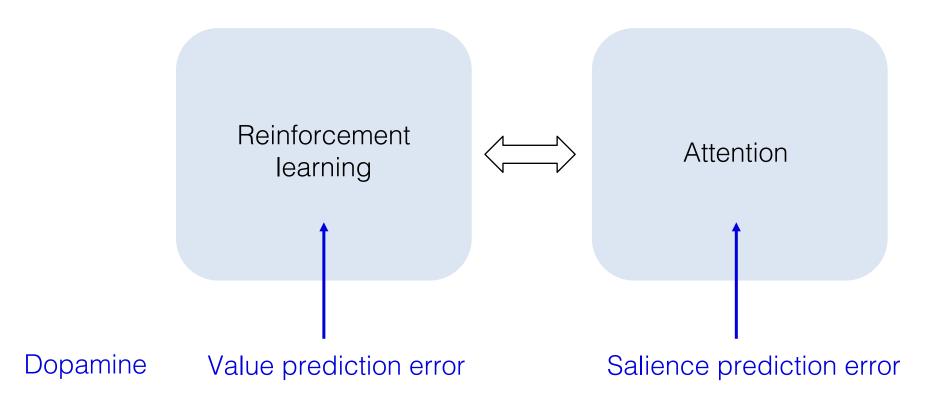
- Defining dopamine signals at different targets.
- What does dopamine do in each target?
   Regulate plasticity, ongoing activity
- Do different regions of the striatum use the same plasticity rule?
- What are the functions of dopamine in each target?

#### Distinct cortico-basal ganglia systems



SPE: salience prediction error

# Dopamine diversity



## Acknowledgements

Uchida lab:

Jeremiah Cohen (Johns Hopkins)

Sebastian Haesler (Leuven University)

Hideyuki Matsumoto (Osaka City University)

Neir Eshel (Stanford University)

Michael Bukwich

Vinod Rao

Vivian Hemmelder

Ju Tian

Sachie Ogawa

William Menegas

Benedicte Babayan

Mitsuko Watabe-Uchida

Samuel Gershman

Christian Machens

Dmitry Kobak

Reagents

Edward Callaway (rabies virus)

Fumitaka Osakada (rabies virus)

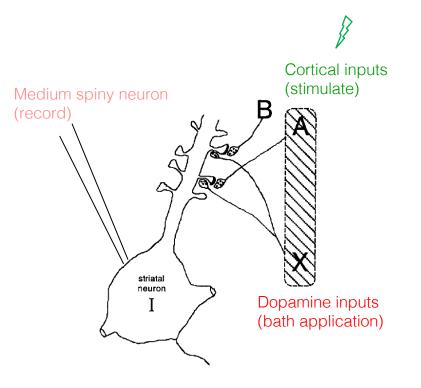
Bradford Lowell (vGAT-Cre)

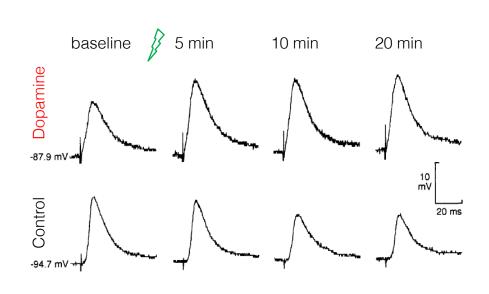
Linh Vong (vGAT-Cre)

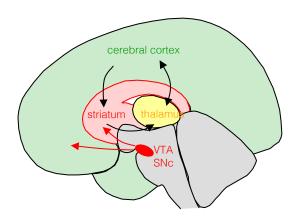
#### **Funding**

National Institute of Mental Health

#### Dopamine regulates neural plasticity in the striatum







membrane potential depolarization

(EPSP: excitatory postsynaptic synaptic potentials)

• With dopamine, depressing synapse gets facillitatory

# A critical time window for dopamine actions on the structural plasticity of dendritic spines

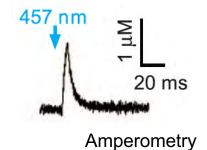
Sho Yagishita,<sup>1,2</sup> Akiko Hayashi-Takagi,<sup>1,2,3</sup> Graham C.R. Ellis-Davies,<sup>4</sup> Hidetoshi Urakubo,<sup>5</sup> Shin Ishii,<sup>5</sup> Haruo Kasai<sup>1,2</sup>\*

Glutamatergic input (ChR2)

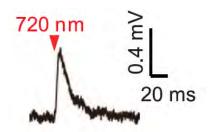
(Glu-uncaging)

(ChR2)

#### **Optogenetics**

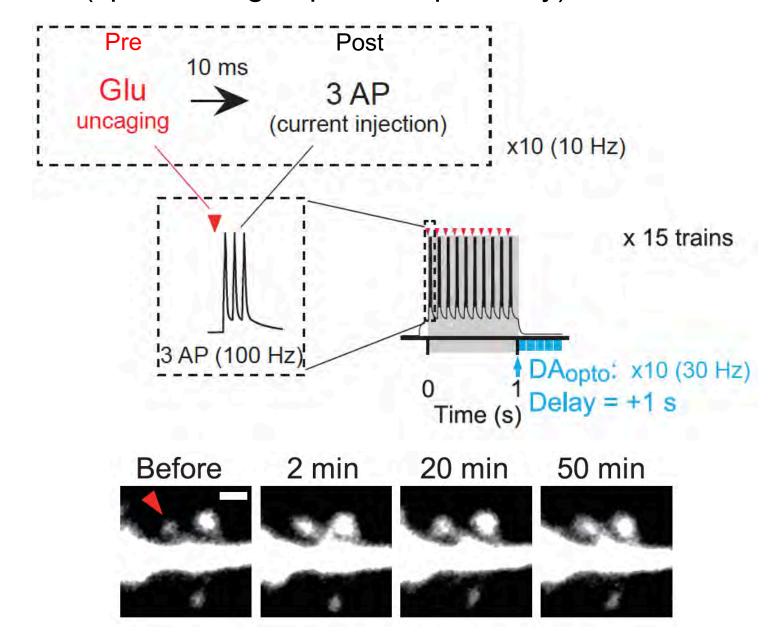


Uncaging

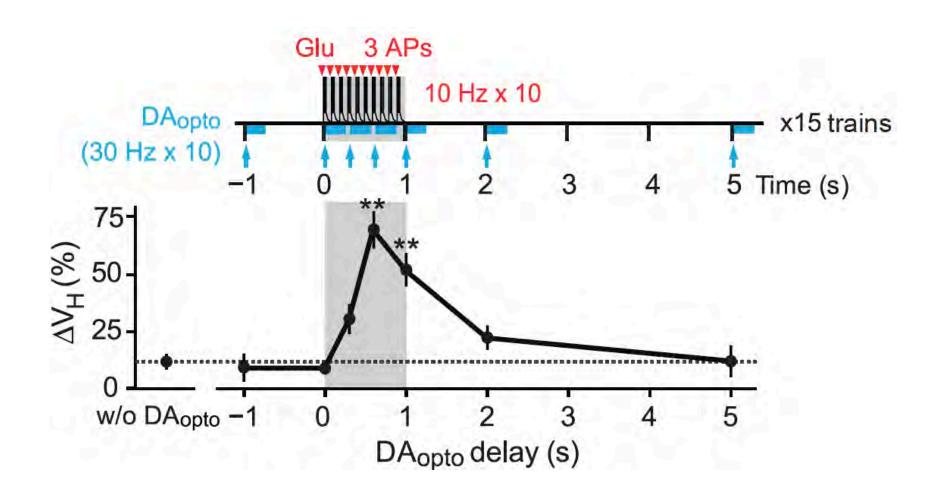


**EPSP** 

STDP (spike-timing dependent plasticity)



#### A window for dopamine reinforcement

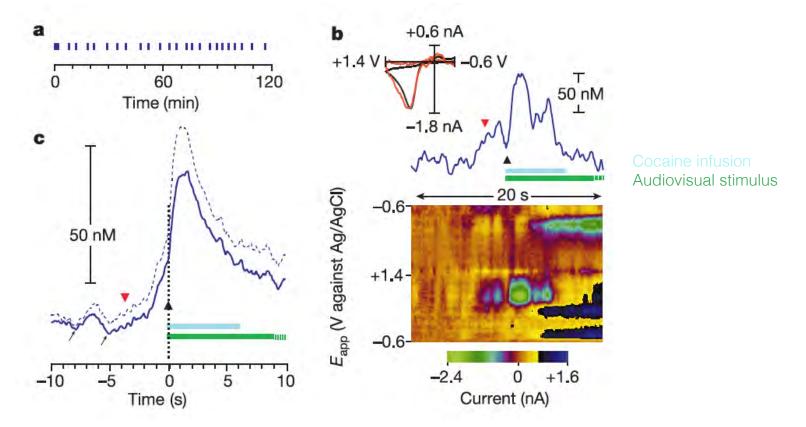


#### Non-canonical firing patterns

### Subsecond dopamine release promotes cocaine seeking

Paul E. M. Phillips\*†‡, Garret D. Stuber‡§, Michael L. A. V. Heien†, R. Mark Wightman†‡§ & Regina M. Carelli\*§

Dopamine increase before initiation of movement

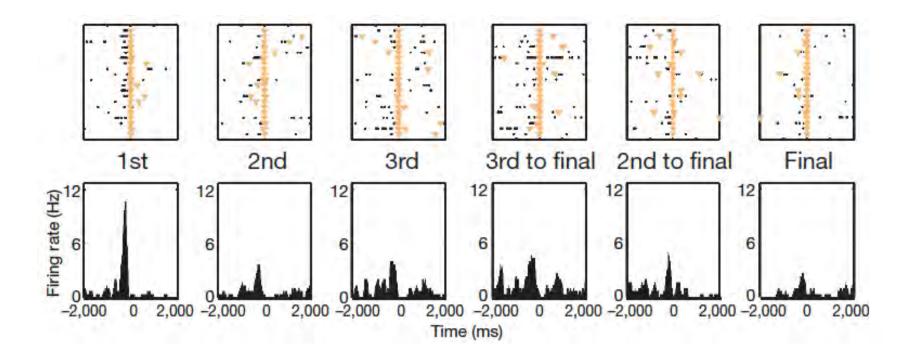


Cyclic voltametry

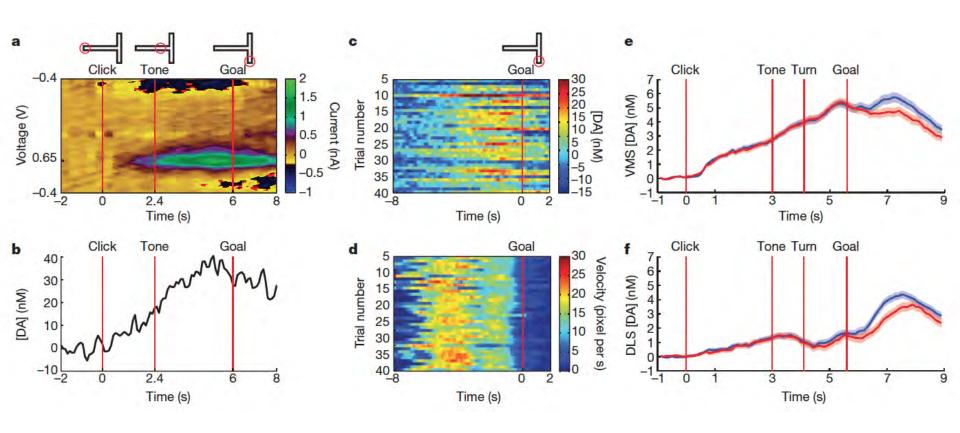
<sup>\*</sup> Department of Psychology, † Department of Chemistry, ‡ Neuroscience Center, and § Curriculum in Neurobiology, University of North Carolina, Chapel Hill, North Carolina 27599, USA

#### Start/stop signal

Mouse performing lever pressing with a fix-ratio (8) schedule



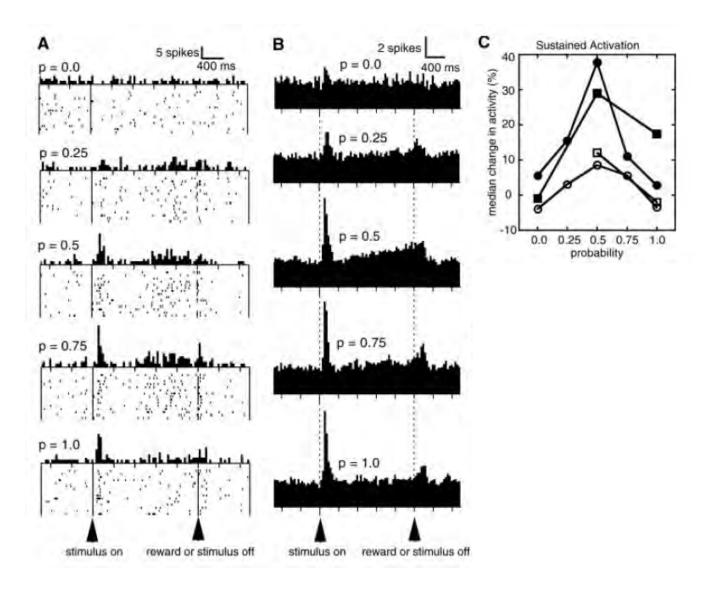
#### Ramping dopamine



- Freely-moving rats
- T-maze
- Cyclic voltammetry

(Howe et al., 2013)

#### Ramping dopamine





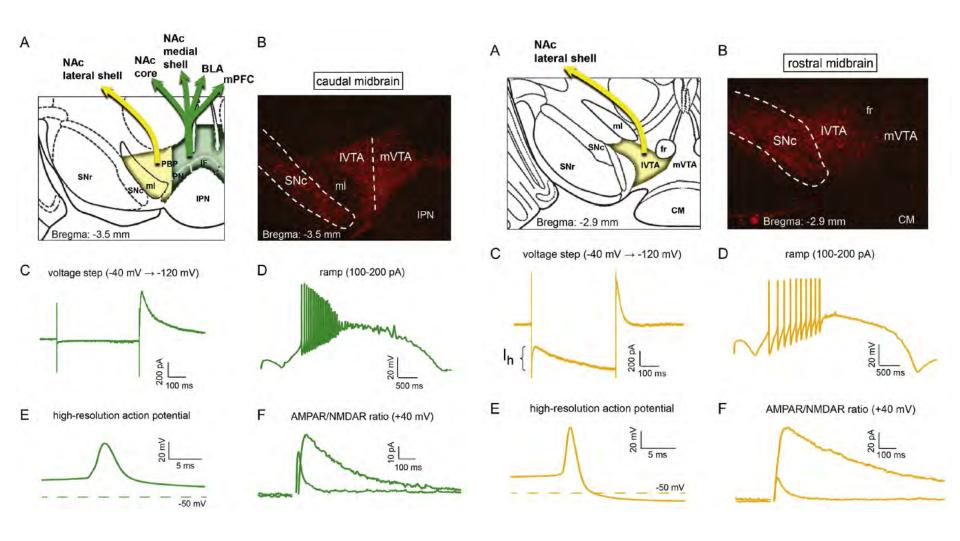


Neuron 57, 760-773, March 13, 2008

### Unique Properties of Mesoprefrontal Neurons within a Dual Mesocorticolimbic Dopamine System

Stephan Lammel, 1,3 Andrea Hetzel, 3,4 Olga Häckel, 3,4 Ian Jones, 3,5 Birgit Liss, 2,3,\* and Jochen Roeper 1,3,\*

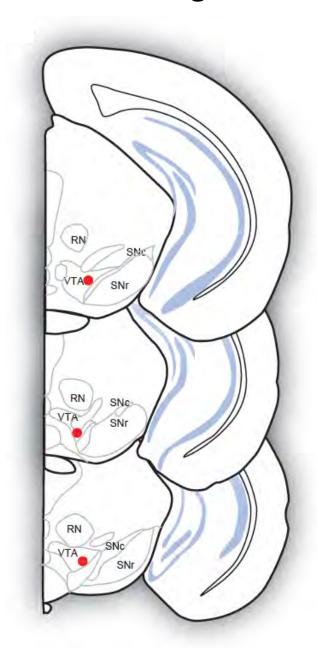
## Dopamine neurons projecting to different areas have different properties



#### Multiple dopamine hypothesis

- Movement initiation/termination
- Reward
- Wanting, seeking
- Pleasure, hedonic
- Prediction error (learning, action selection)
- Salience/attention
- Incentive salience
- Motivation/energizing behavior
- Uncertainty
- Cost/benefit computation

### Recording sites



#### Origins of dopamine projections

