Computational models of addiction

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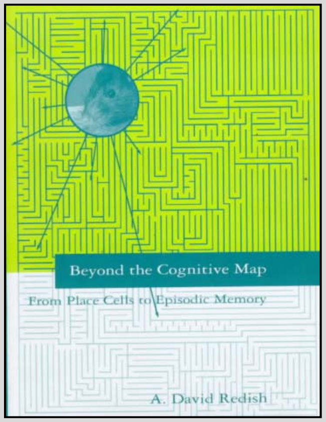

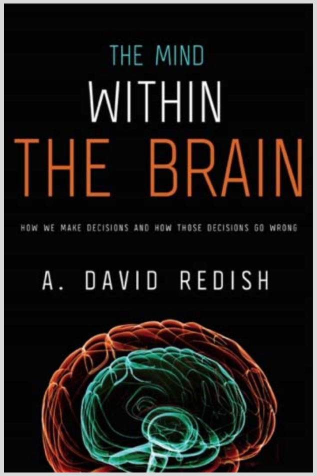

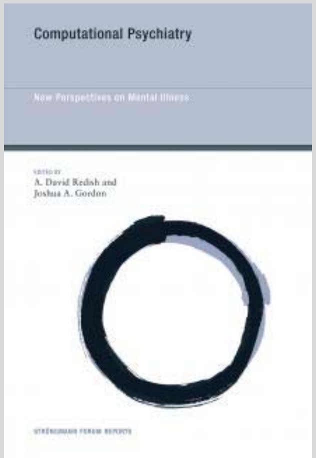

Computational models of addiction

assessing models and consequences

We're going to be talking about mechanistic models.

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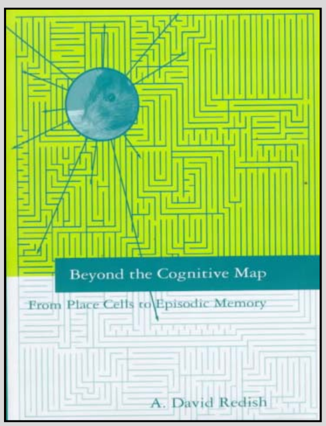
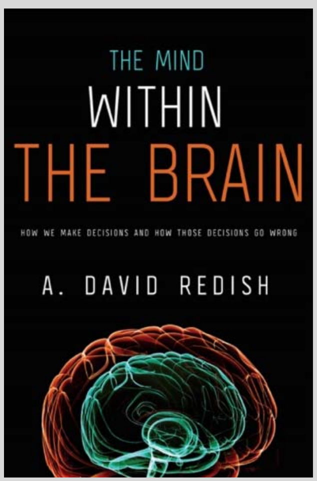




The concept of the "failure mode"

"Failure modes"

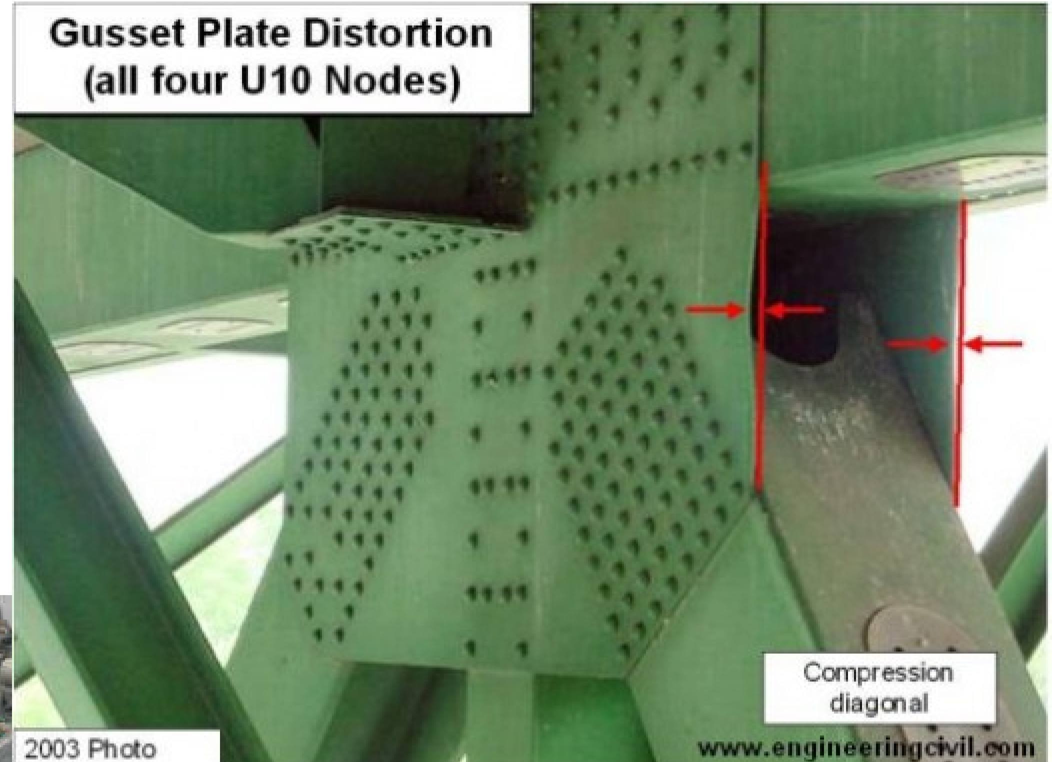
In engineering, a "failure mode" is a vulnerability inherent in the machinery.

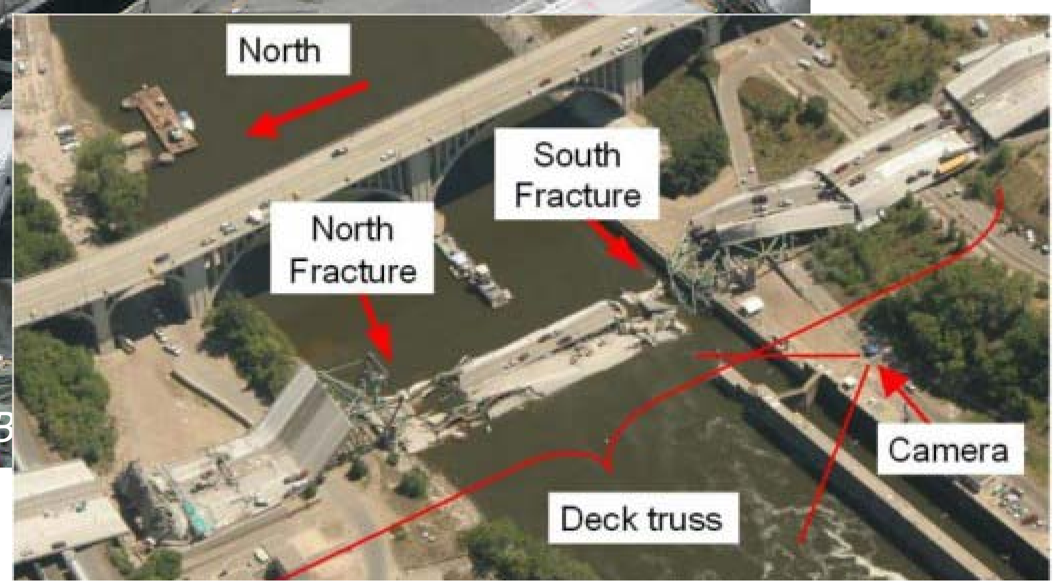
35W Bridge Collapse, 2007. startribune.com

The concept of the "failure mode"

In engineering, a "failure mode" is a vulnerability inherent in the machinery.

"Failure modes"





A concrete example of a failure mode

REPORTS

Addiction as a Computational Process Gone Awry

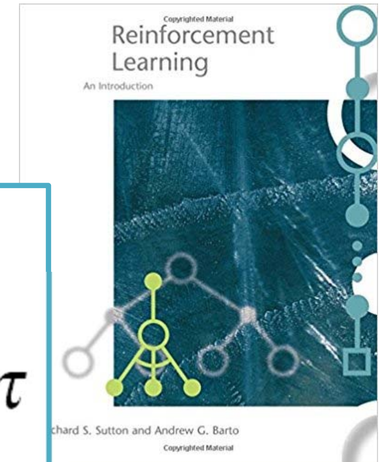
A. David Redish

10 DECEMBER 2004 VOL 306 SCIENCE www.sciencemag.org

The delta signal

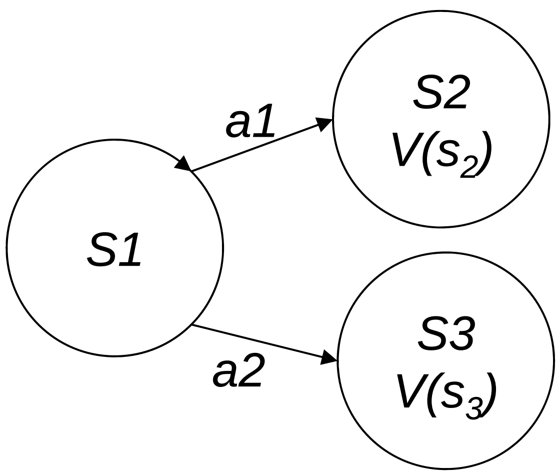
"Failure modes"

Given a choice, if we learn the value of our choices, we can make decisions based on those learned values.



Define "value" as the total expected (discounted) reward.

$$V(t) = \int_t^{\infty} \mathrm{disc}(E[R(\tau)], \tau - t) d\tau$$



We can learn the value from the ***value prediction error*** *signal δ.*

$$\delta(t) = \gamma^{d}(R(S_l) + V(S_l)) - V(S_k)$$

$$V(S_k) \leftarrow V(S_k) + \eta_V \cdot \delta$$

Dopamine as delta

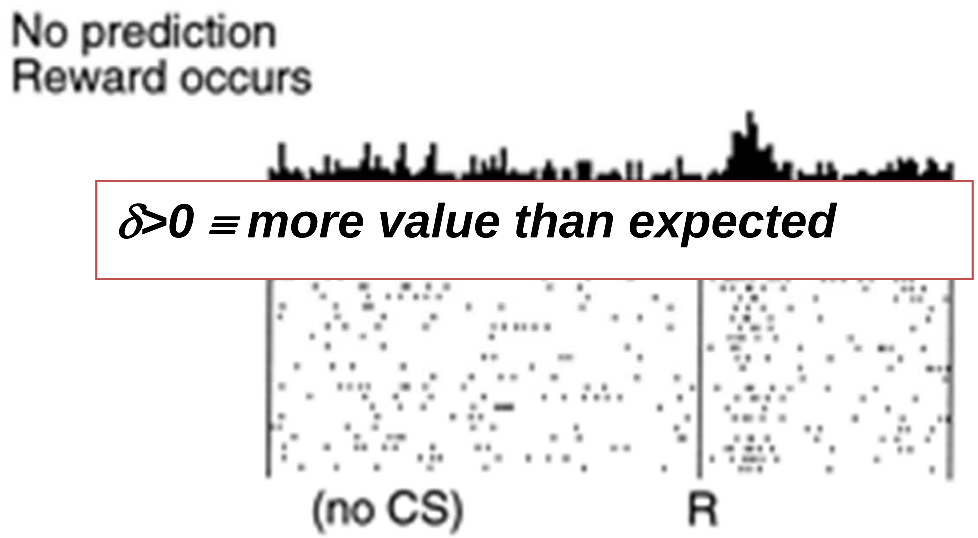
Phasic dopamine signals appear to track δ surprisingly well.

A Neural Substrate of Prediction and Reward

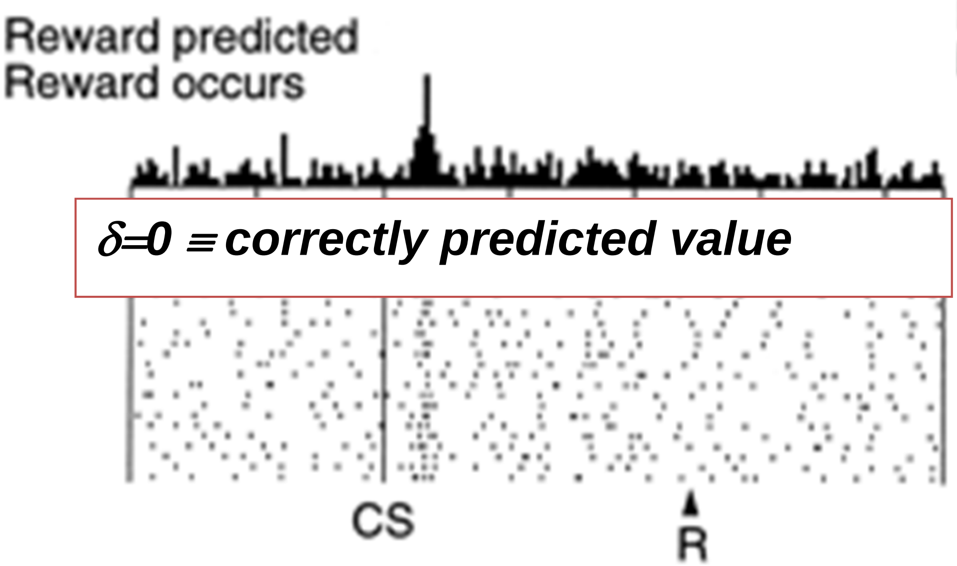
Wolfram Schultz, Peter Dayan, P. Read Montague*

+ See all authors and affiliations

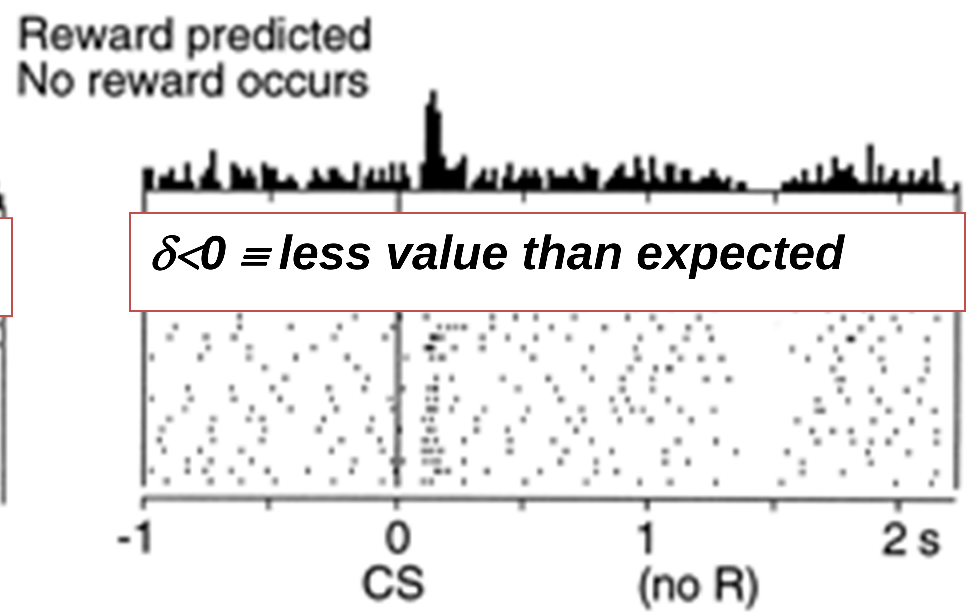
Science 14 Mar 1997:
Vol. 275, Issue 5306, pp. 1593-1599
DOI: 10.1126/science.275.5306.1593



δ>0 $\equiv$ more value than expected



δ=0 $\equiv$ correctly predicted value



δ<0 $\equiv$ less value than expected

What if dopamine **is** delta?

What if dopamine **is** delta?

Hypothesis

Dopamine = value prediction-error (δ) in reinforcement learning.

Hypothesis

(Some) drugs of abuse produce dopamine neuropharmacologically.

Implication

Drugs of abuse produce non-compensable value prediction error (δ) signals.

$$\delta = \max(\gamma^d (R(S_l) + V(S_l)) - V(S_k) + D(S_l), D(S_l))$$

Conclusion

At least part of the addictive process is caused by this non-compensable dopamine signal.

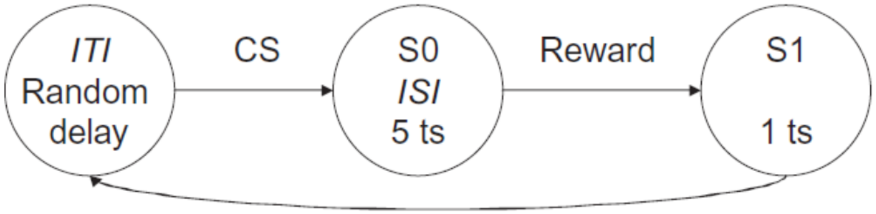
Addiction as a computational process gone awry

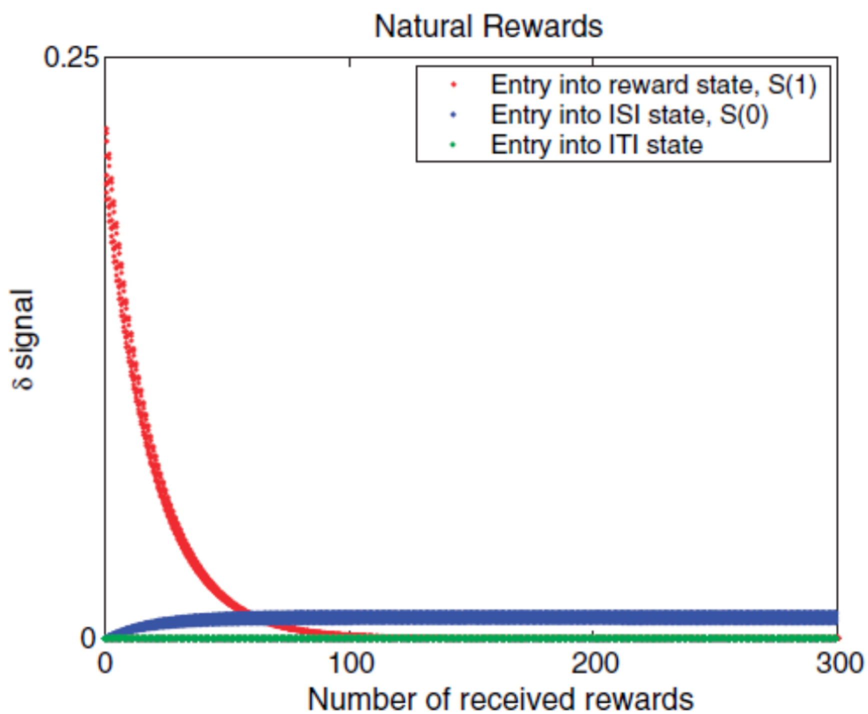
In normal TDRL, learning drives δ to 0, but in this equation δ ≥ D.

"Failure modes"

Redish (2004) Science

$$\delta = \max(\gamma^{d}(R(S_l)+V(S_l)) - V(S_k) + D(S_l), D(S_l))$$





Addiction as a computational process gone awry

“Failure modes”

Redish (2004) Science

A non-compensable dopamine signal would…

1. Increase the likelihood of taking drugs over alternatives

2. Make drugs inelastic

3. Not show Kamin blocking

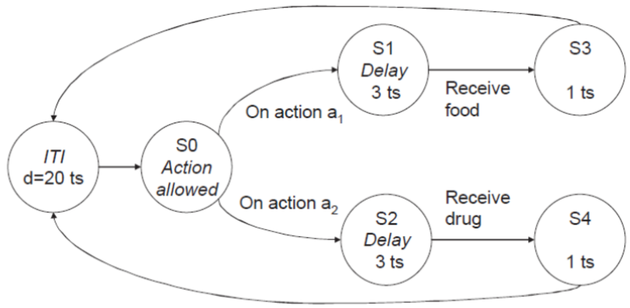
Addiction as a computational process gone awry

A non-compensable dopamine signal would…

1. **Increase the likelihood of taking drugs over alternatives**
2. Make drugs inelastic
3. Not show Kamin blocking

"Failure modes"

Redish (2004) Science



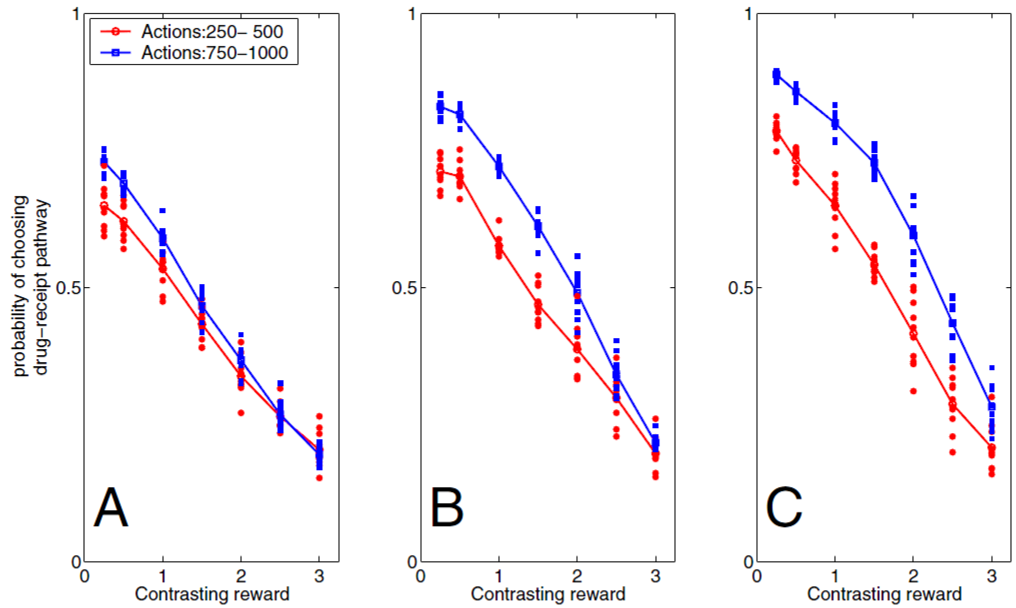


FIGURE S2: Sensitivity of selection to number of drug experiences, size of contrasting food reward, and size of drug-receipt forced-dopamine signal (i.e. strength/dose of the drug). (**A**) $R(S_4) = 1.0, D(S_4) = 0.010$; (**B**) $R(S_4) = 1.0, D(S_4) = 0.025$; (**C**) $R(S_4) = 1.0, D(S_4) = 0.040$.

Addiction as a computational process gone awry

A non-compensable dopamine signal would…

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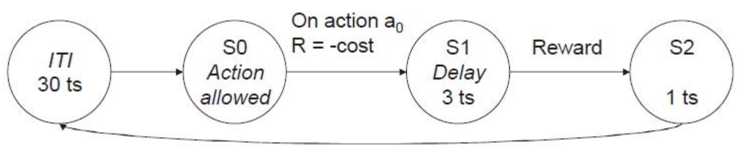
"Failure modes"

Redish (2004) Science



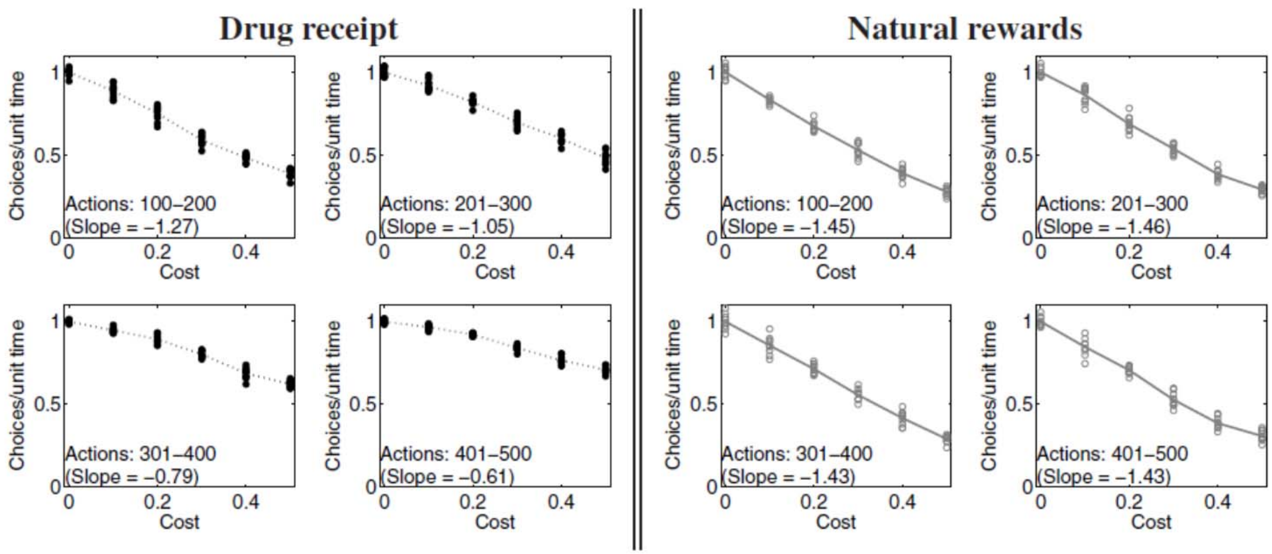


FIGURE S4: Elasticity decreases for drug-receipt but not reward-receipt.

Addiction as a computational process gone awry

A non-compensable dopamine signal would…

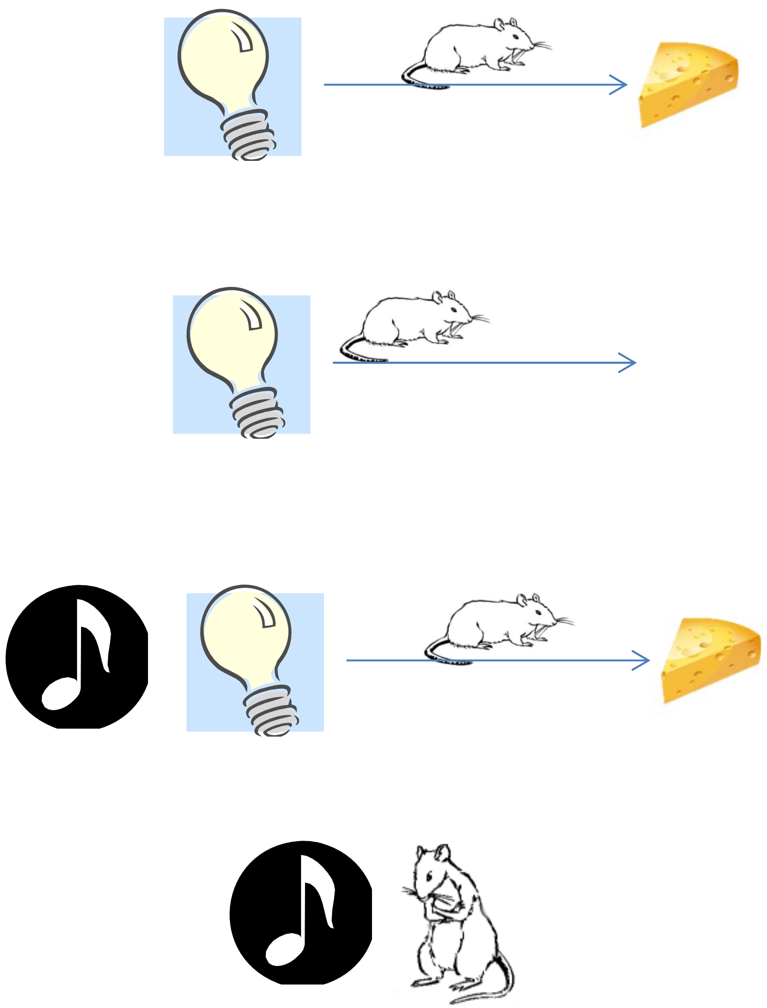
1. Increase the likelihood of taking drugs over alternatives

2. Make drugs inelastic

3. **Not show Kamin blocking**

"Failure modes"

Kamin 1969



Addiction as a computational process gone awry

A non-compensable dopamine signal would…

1. Increase the likelihood of taking drugs over alternatives

2. Make drugs inelastic

3. **Not show Kamin blocking**

"Failure modes"

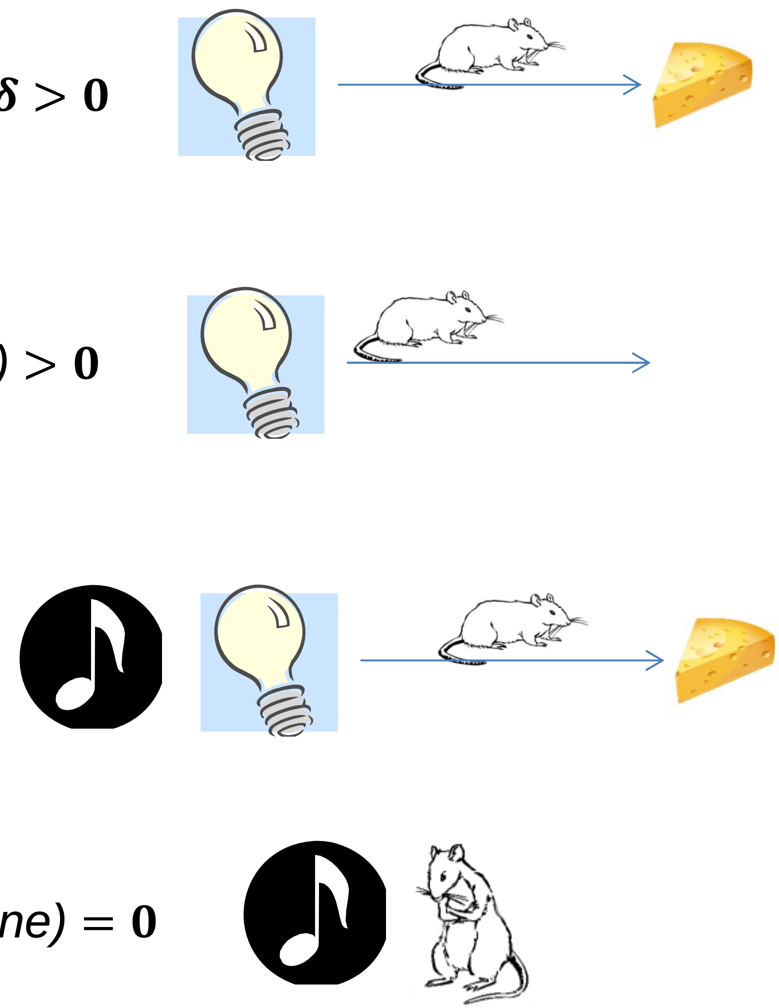
$$\delta(t) = \gamma^d (R(S_l) + V(S_l)) - V(S_k)$$

$\boldsymbol{\delta > 0}$

$V(light) > \mathbf{0}$

$\boldsymbol{\delta = 0}$

$V(tone) = \mathbf{0}$



Addiction as a computational process gone awry

A non-compensable dopamine signal would…

1. Increase the likelihood of taking drugs over alternatives
2. Make drugs inelastic
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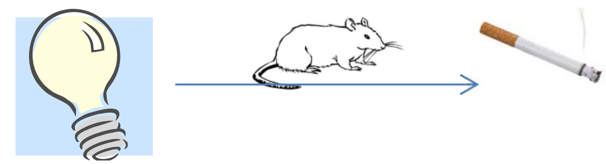
"Failure modes"

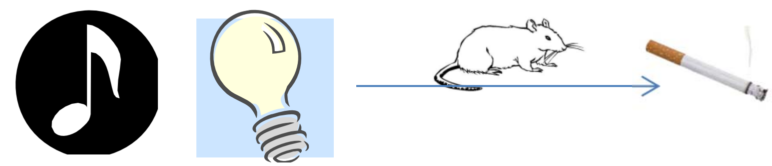
$$\delta = \max(\gamma^d (R(S_l) + V(S_l)) - V(S_k) + D(S_l), D(S_l))$$

$\boldsymbol{\delta > 0}$

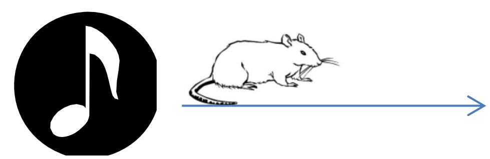


$V(light) > \mathbf{0}$

$\boldsymbol{\delta > 0}$



$V(tone) > \mathbf{0}$



Addiction as a computational process gone awry

A non-compensable dopamine signal would…

1. Increase the likelihood of taking drugs over alternatives
2. Make drugs inelastic
3. **Not show Kamin blocking**

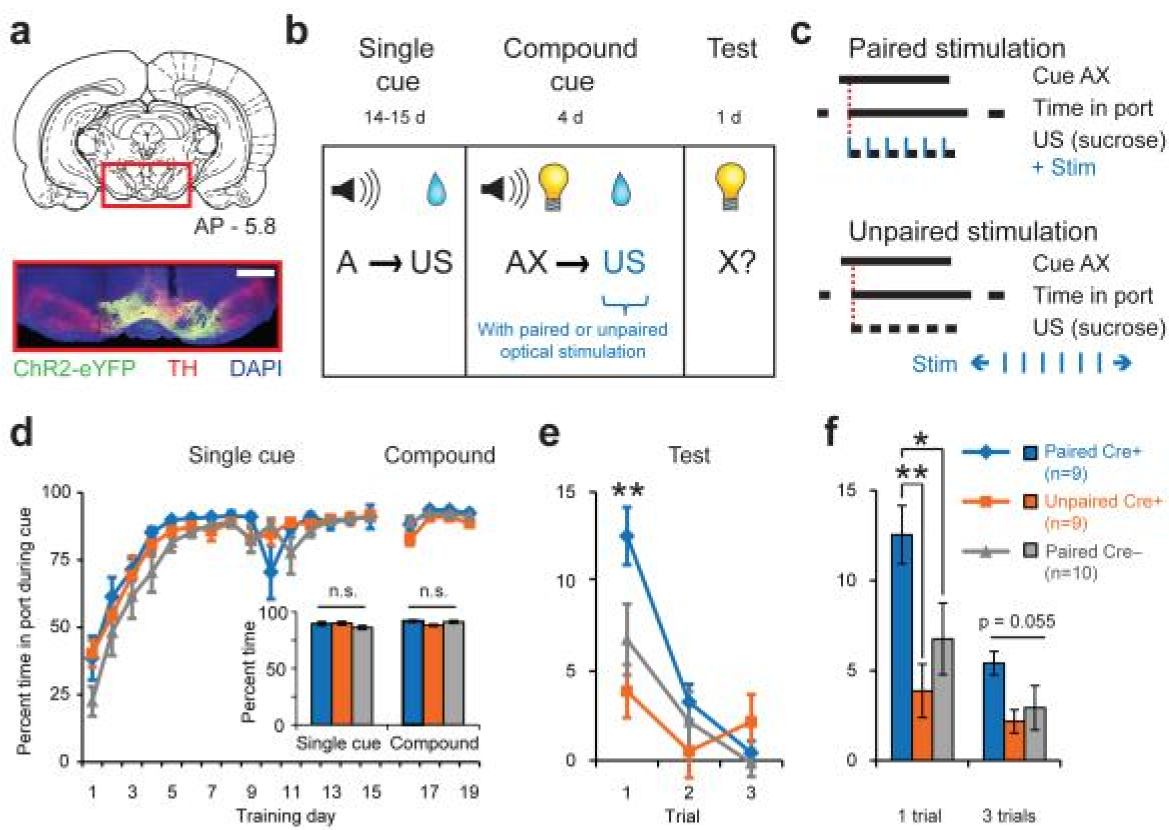
"Failure modes"

A causal link between prediction errors, dopamine neurons and learning

nature neuroscience

Elizabeth E Steinberg[1,2,11], Ronald Keiflin[1,11], Josiah R Boivin[1,2], Ilana B Witten[3,4], Karl Deisseroth[5–8] & Patricia H Janak[1,2,9,10]

Direct manipulations of dopamine disrupt blocking.



Addiction as a computational process gone awry

A non-compensable dopamine signal would…

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"Failure modes"


Available online at www.sciencedirect.com

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Pharmacology, Biochemistry and Behavior 86 (2007) 774–777

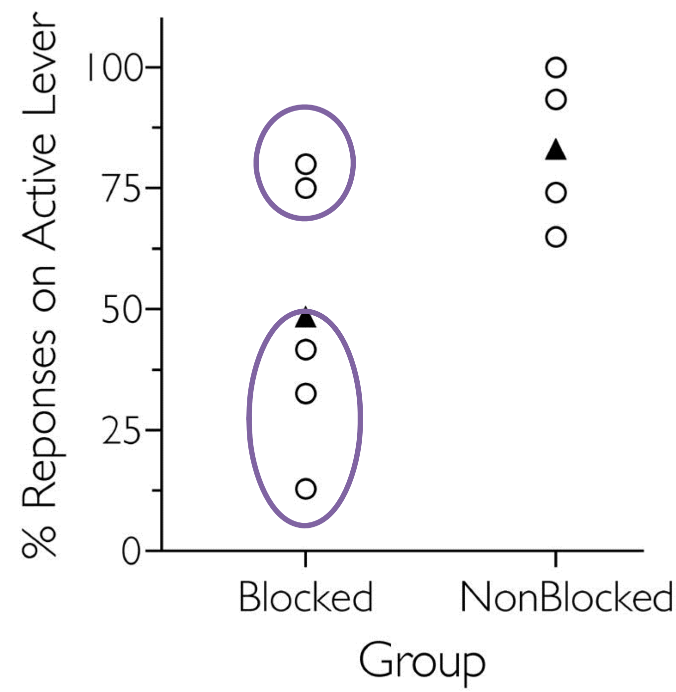
PHARMACOLOGY BIOCHEMISTRY AND BEHAVIOR

www.elsevier.com/locate/pharmbiochembeh

Blocking of conditioning to a cocaine-paired stimulus: Testing the hypothesis that cocaine perpetually produces a signal of larger-than-expected reward

Leigh V. Panlilio *, Eric B. Thorndike, Charles W. Schindler

But cocaine does not block.



Addiction as a computational process gone awry

A non-compensable dopamine signal would…

1. Increase the likelihood of taking drugs over alternatives

2. Make drugs inelastic

3. **Not show Kamin blocking**

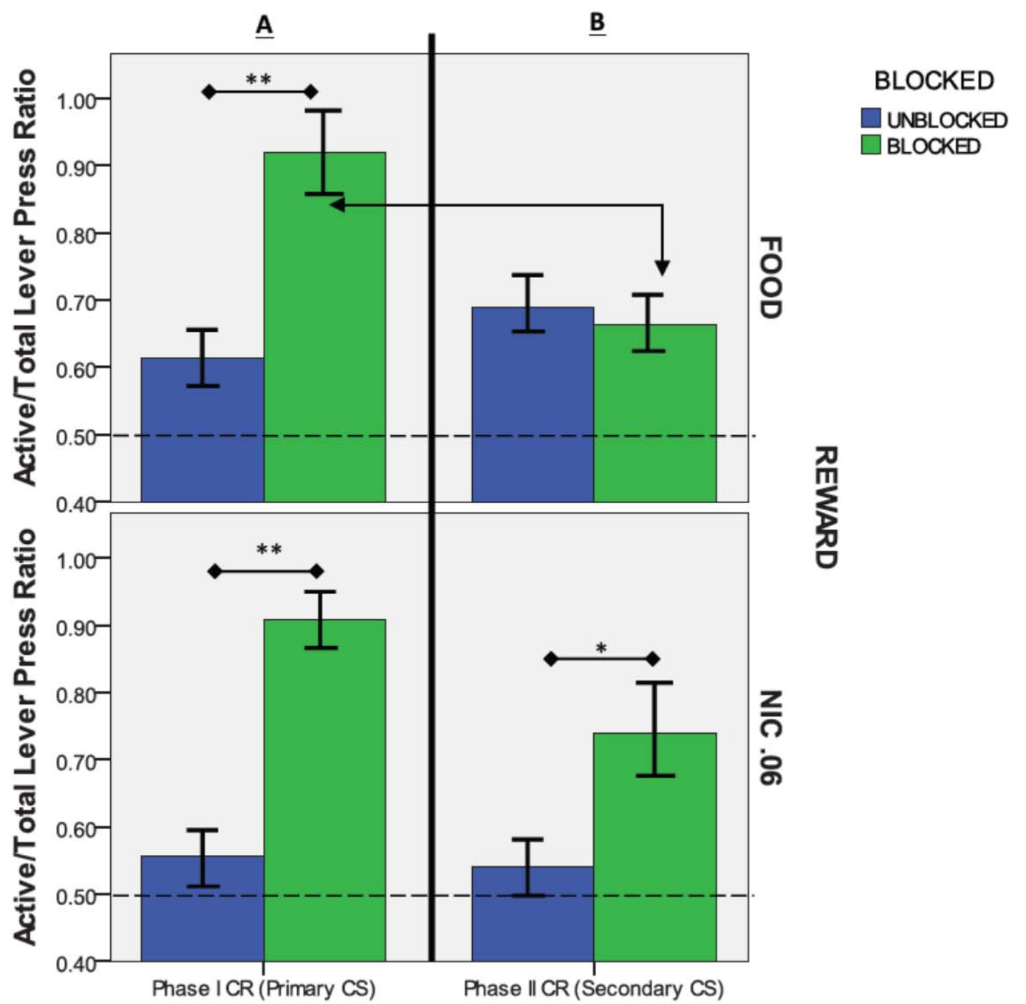
When Jaffe et al looked at the high-responders only, they saw no blocking to nicotine.

"Failure modes"

8 The Open Addiction Journal, 2014, 7, 8-16 Open Access

The Absence of Blocking Innicotine High-Responders as a Possible Factor in the Development of Nicotine Dependence?

Adi Jaffe*[,1], J. Aurora Z. Pham[1], Igal Tarash[1], Sasha S. Getty[1], Michael S. Fanselow[1] and J. David Jentsch[1,2]

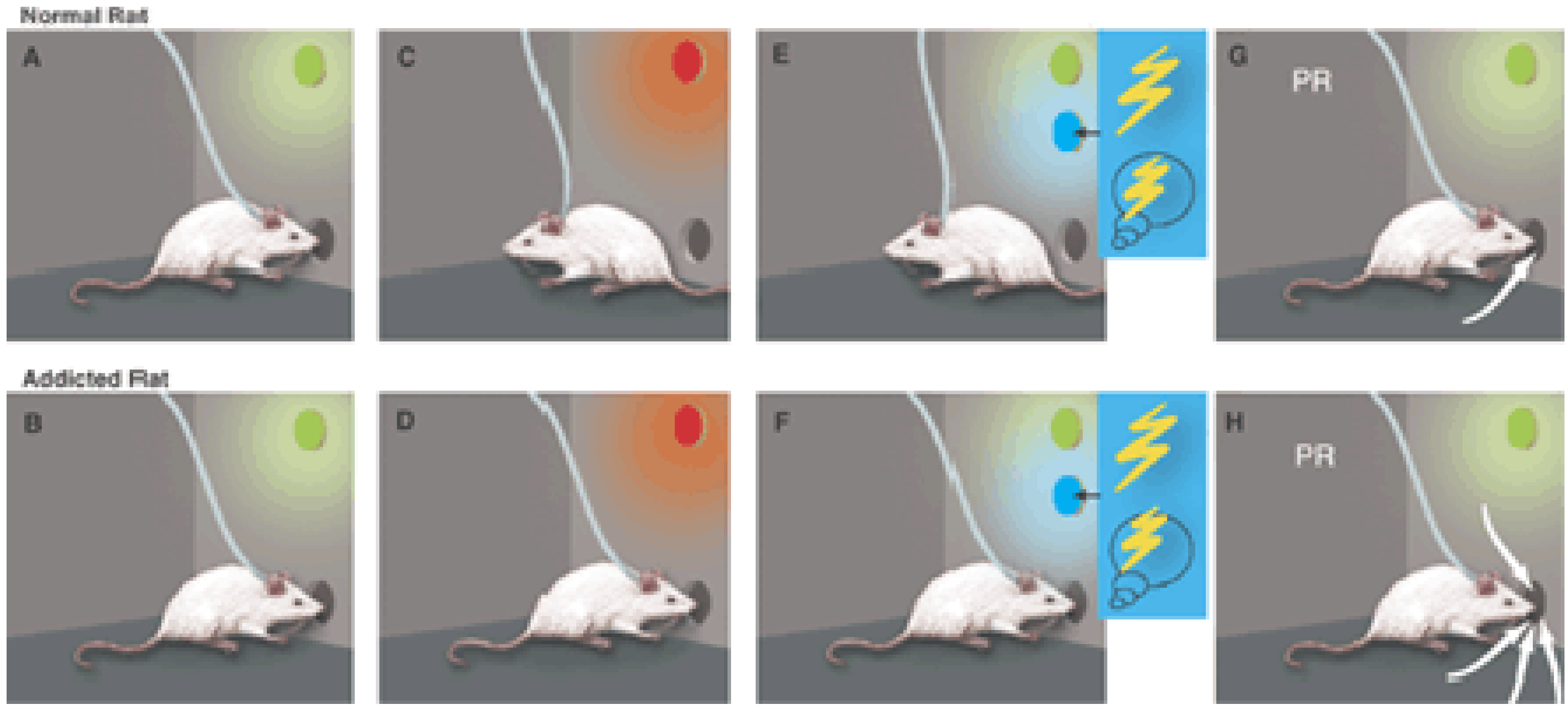


Note: The dashed line represents the point at which active presses = inactive presses
* $p < 0.05$
** $p < 0.01$

Addiction ≠ drug use

Not everyone who takes drugs is addicted.

"Failure modes"



Not all failure modes are habits

From addiction to computational psychiatry

This is but one failure mode of decision that can lead to addiction.

Addiction is a symptom, not a disease.

BEHAVIORAL AND BRAIN SCIENCES (2008) **31**, 415–487
Printed in the United States of America
doi:10.1017/S0140525X0800472X

A unified framework for addiction: Vulnerabilities in the decision process

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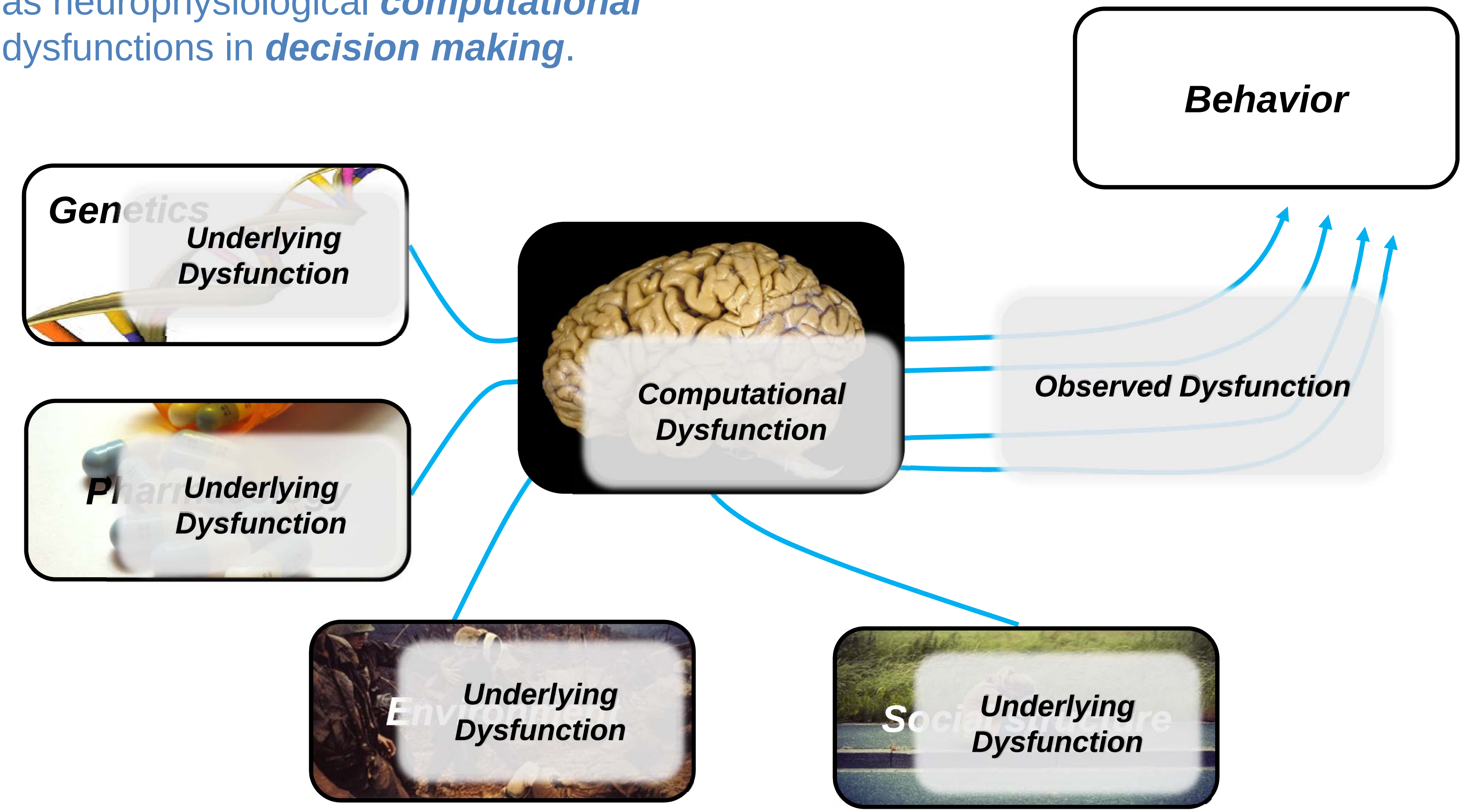
Computational Psychiatry

We need to understand **how** decision-making works to begin to understand how it can go wrong.

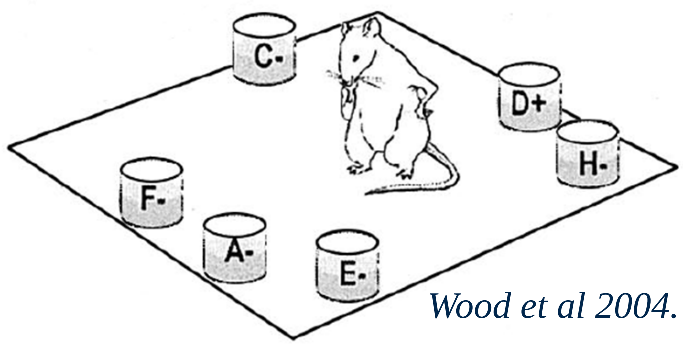
This suggests a new view on psychiatry as neurophysiological ***computational*** dysfunctions in ***decision making***.



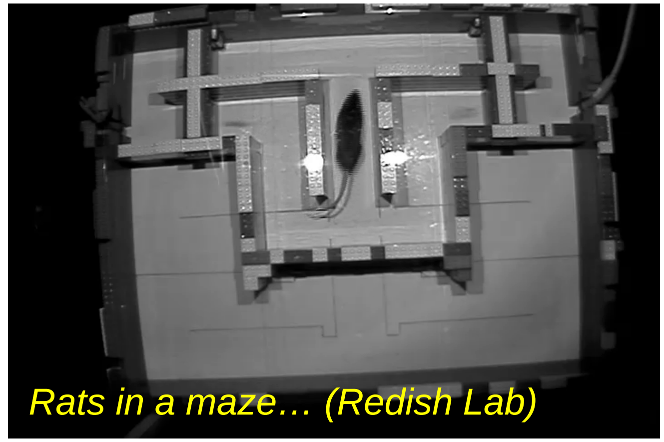
Let us operationalize decision-making as the process that leads to selecting an action.

Decision-making systems

What action should I take when?

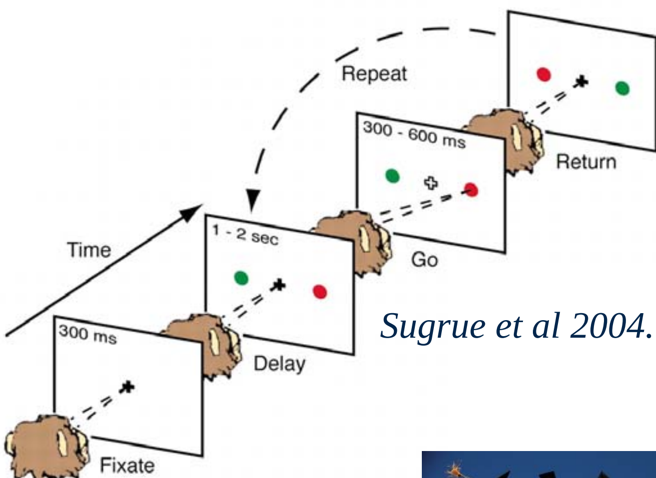


Wood et al 2004.



Rats in a maze… (Redish Lab)

Vending machines



Sugrue et al 2004.

Gambling

Taking drugs…
or not…

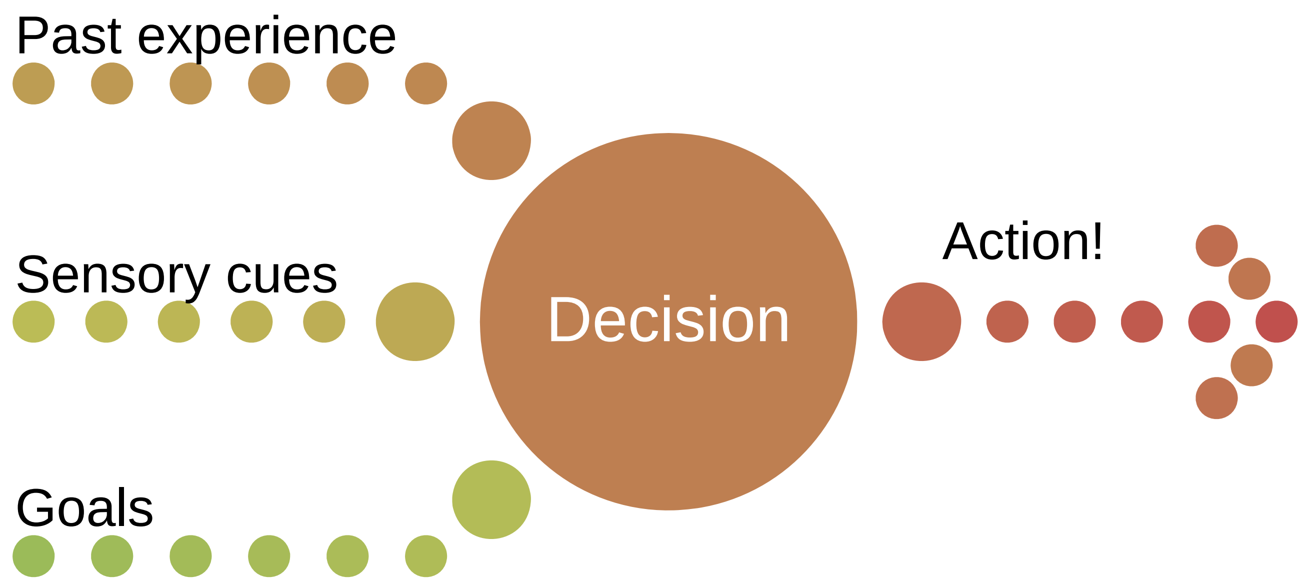
Where to go
to college

Getting married…

Decision-making systems

Computation

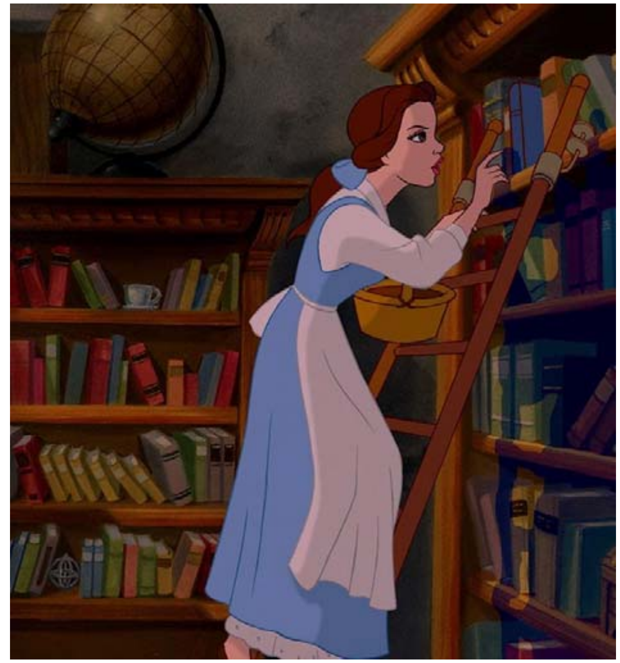
Decision-making is about information processing.



The computational perspective

How you represent the data changes the calculation

Sorted by author

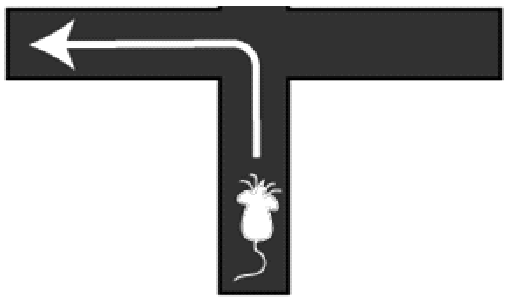


Sorted by size

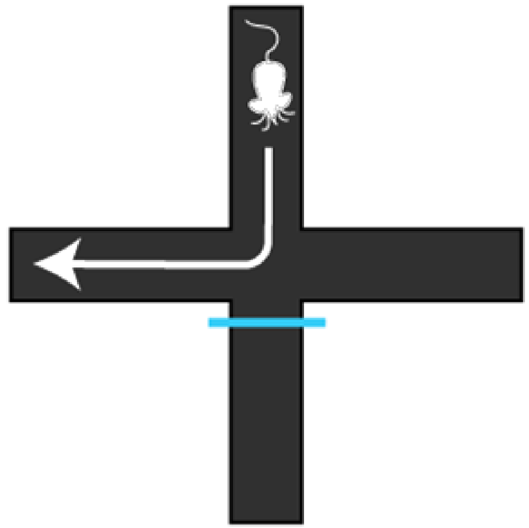
University of Minnesota

The “correct” outcome
can change, depending on how
you represent the data

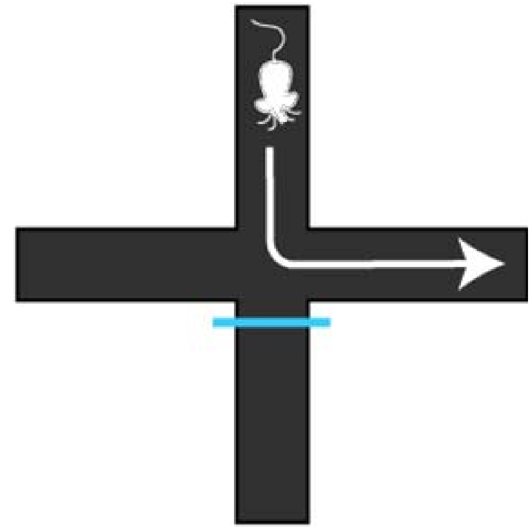
The computational perspective



Probe trials

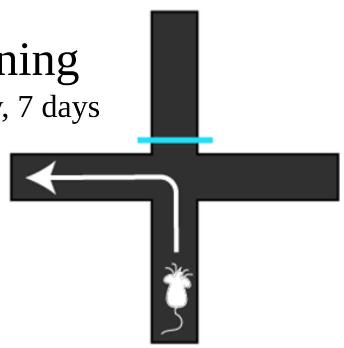


Place-strategy
(return to same location
by taking a different action)



Response-strategy
(turn in same direction
but reach a different goal)

Training
4x/day, 7 days

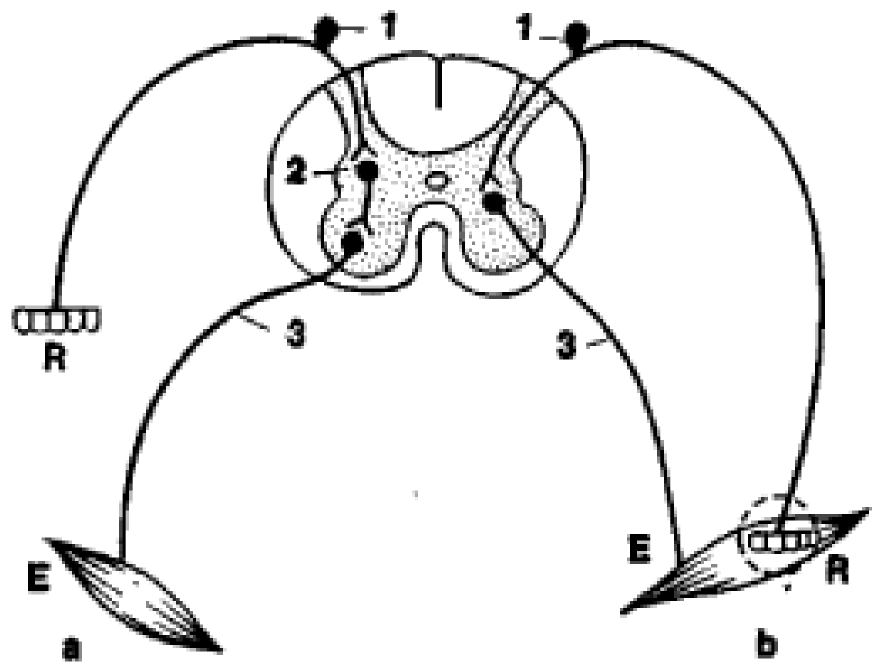


Reflexes

Reflexes: prewired responses to stimuli.

Goals and stimulus-action pairs are learned over an *evolutionary timescale*.

Learning within the lifespan is limited to habituation, sensitization, and other simple threshold adjustments.



Instinctual action-selection systems

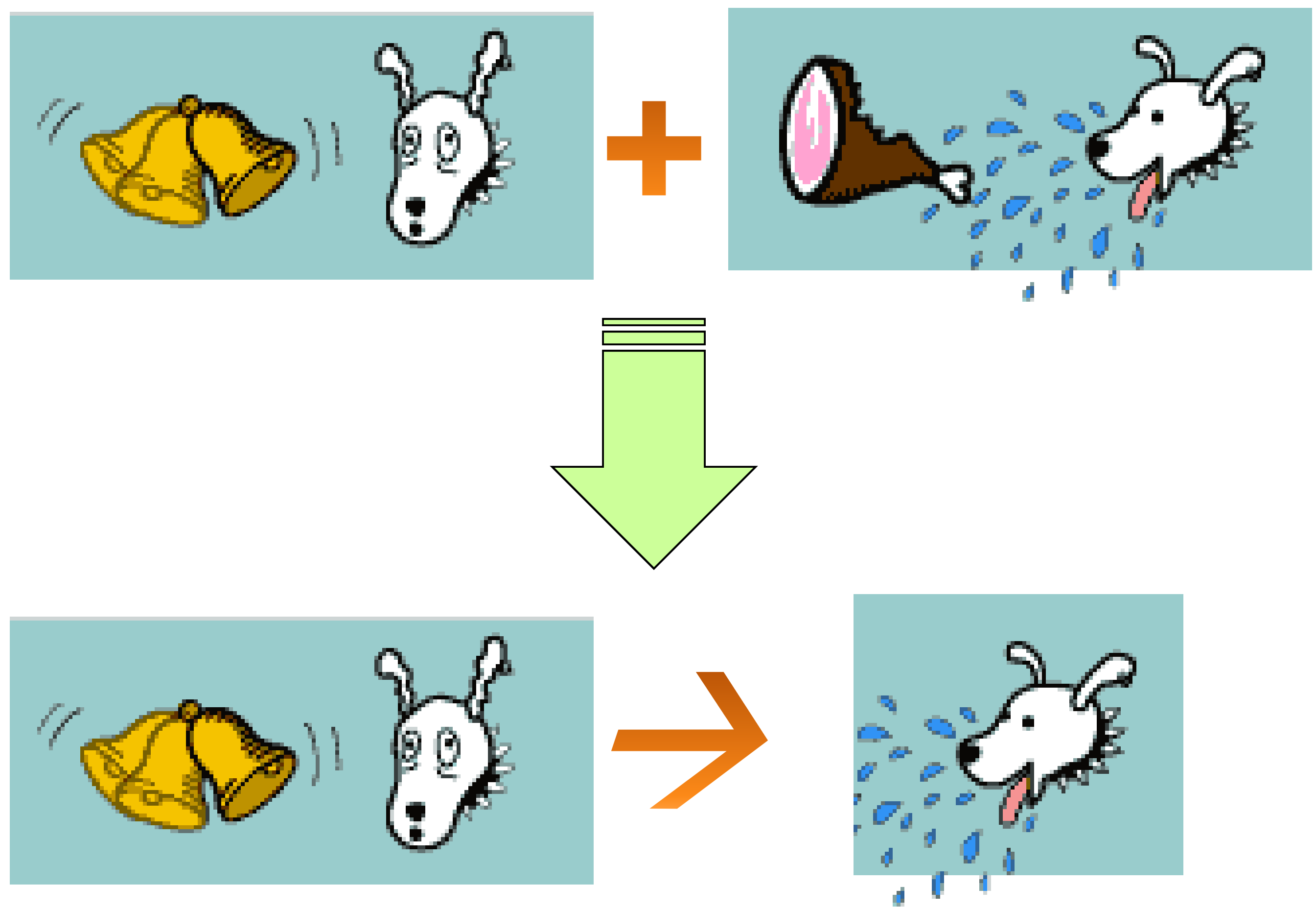
Decision-making systems

Reflexes: prewired responses to stimuli.

Learning to release prewired actions under the right conditions.

Emotionally driven.

Instinctual (Pavlovian, emotional): learning the situation to release prewired actions.



Deliberation

Decision-making systems

Reflexes: prewired responses to stimuli.

Pavlovian (emotional): learning the situation to release prewired actions.

Deliberation: search and evaluate potential consequences.

Searching through potential outcomes.

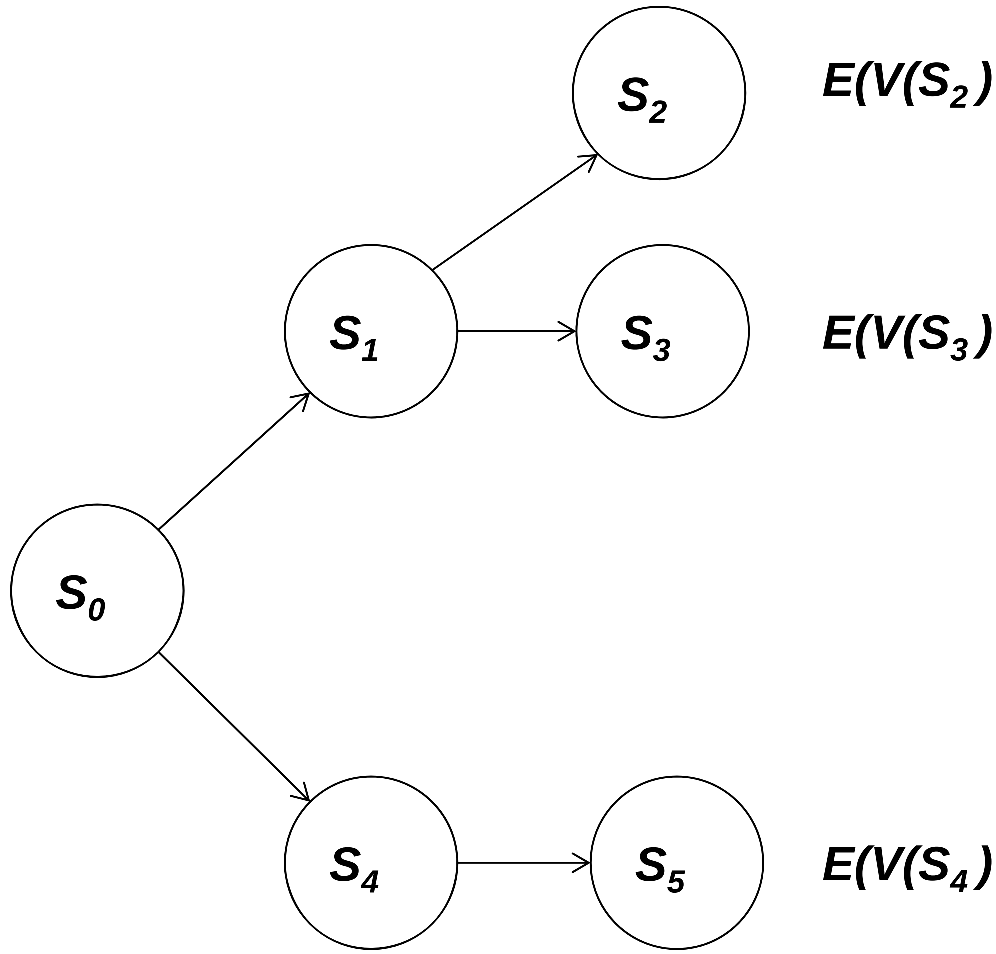
Cognitively and computationally expensive.

Requires mental time travel.

Models

Current models of planning suggests that prefrontal-hippocampal interactions allow the creation of *simulated worlds* that are subsequently *evaluated*.

"Failure modes"



We can see failure modes of expectation.

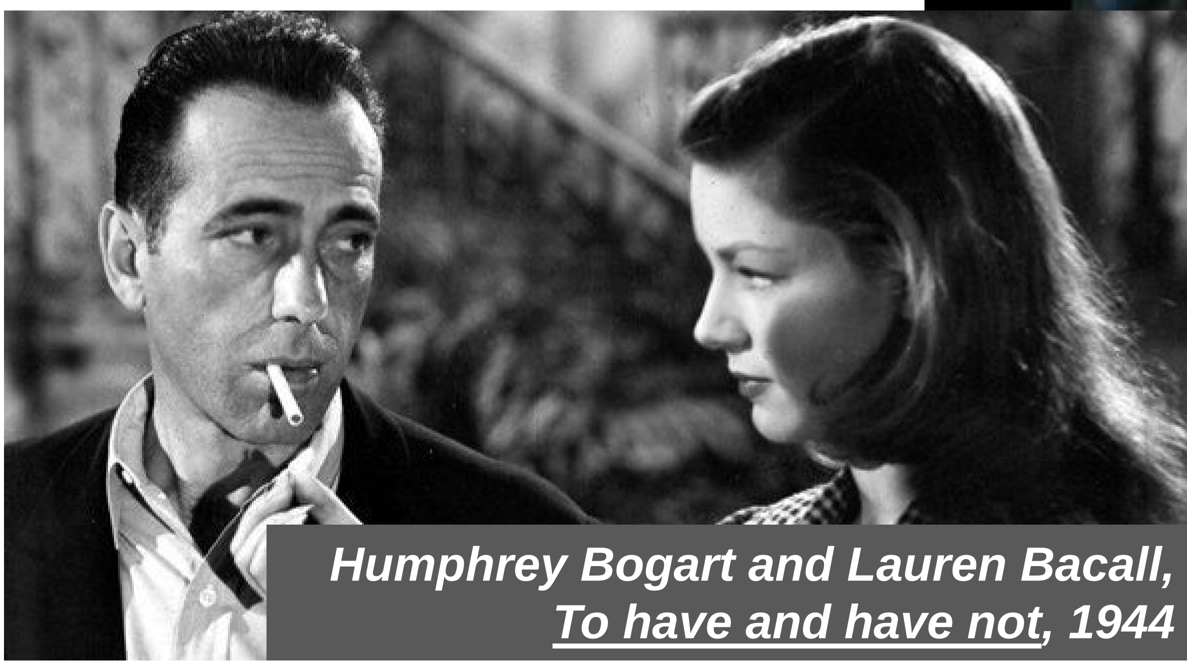
Or of evaluation.

Failure modes of expectation

"Failure modes"

"cigarettes are cool"

Joe Camel advertising to kids, 1987-1997



Humphrey Bogart and Lauren Bacall, <u>To have and have not</u>, 1944

Procedural Habits

Reflexes: prewired responses to stimuli.

Instinctual: learning the situation to release prewired actions.

Deliberation: search and evaluate potential consequences.

Procedural (habits): cached action-chain sequences.

Decision-making systems

Fast but inflexible.

Learned slowly.

Lauren Gibbemeyer

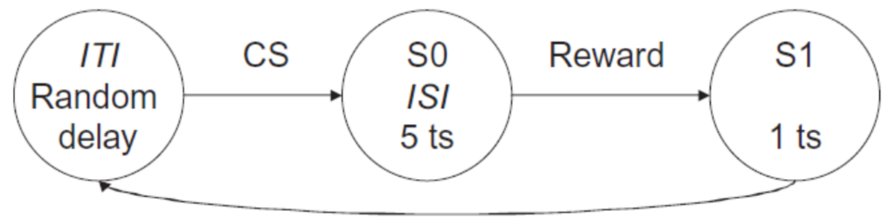
Addiction as a computational process gone awry

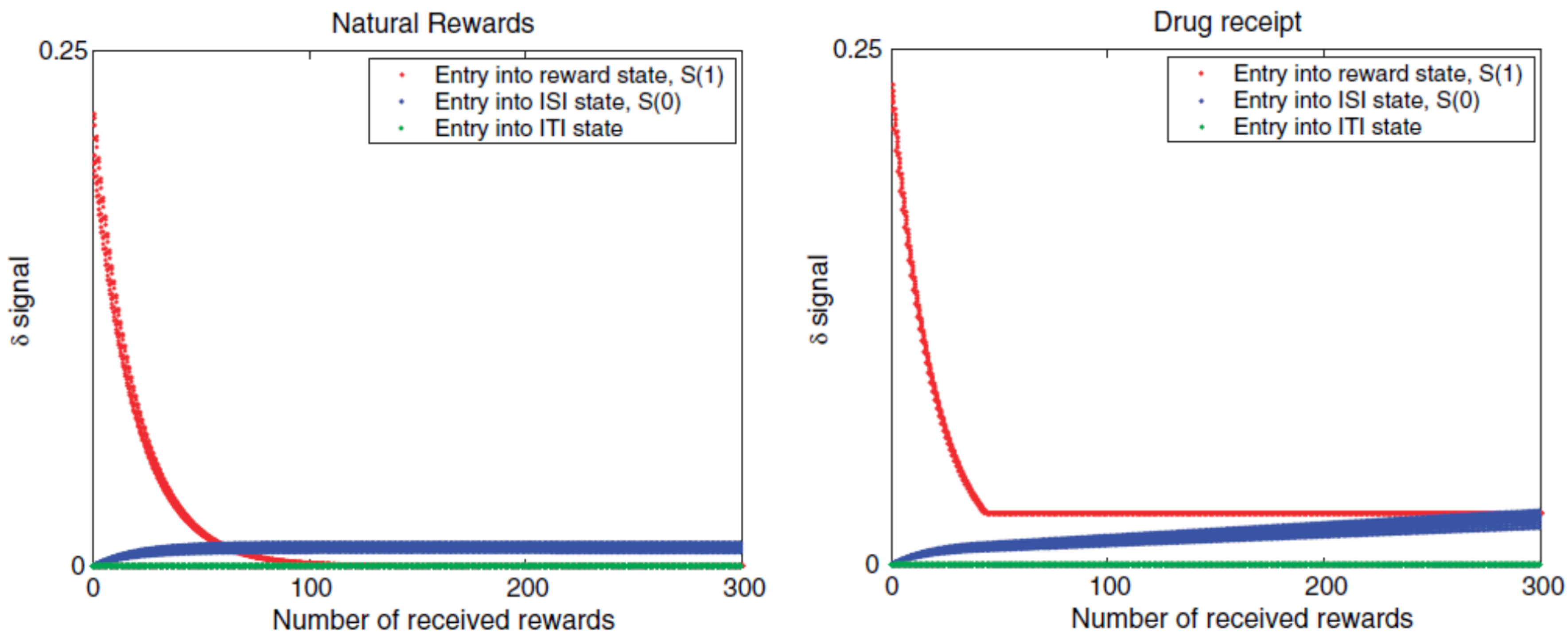
"Failure modes"

Redish (2004) Science

In normal TDRL, learning drives δ to 0, but in this equation $\delta \geq D$.

$$\delta = \max(\gamma^{d}(R(S_l)+V(S_l))-V(S_k)+D(S_l),D(S_l))$$





Decision-making systems

PERCEPTION

Integrating information…

SITUATION RECOGNITION

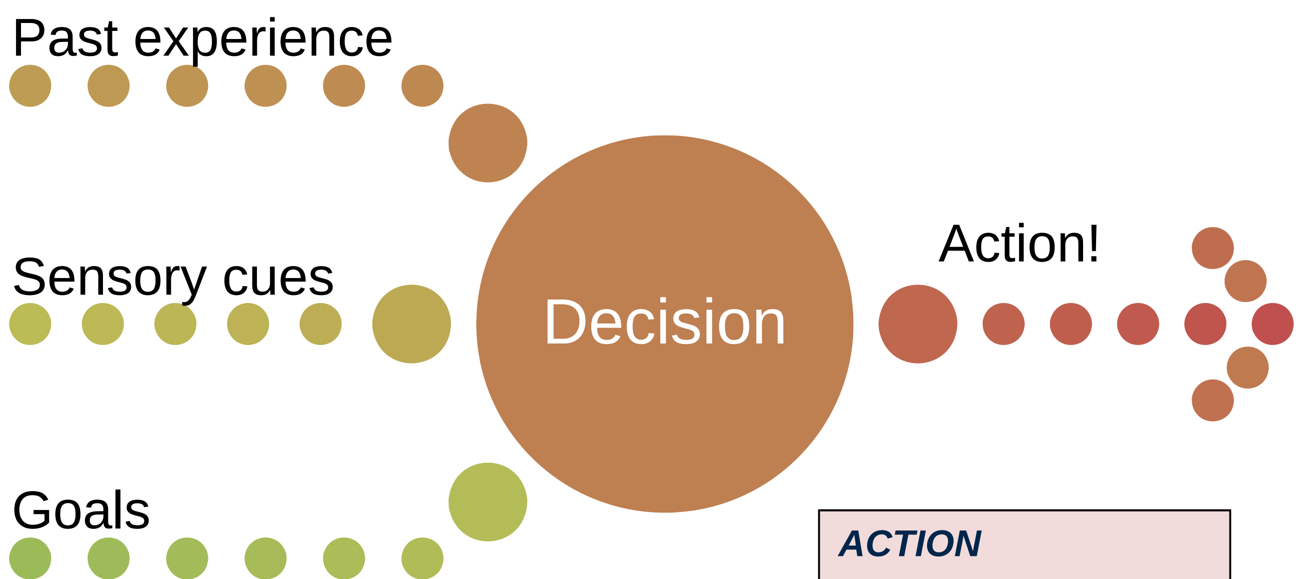
Classification of the situation by cortical prototype mechanisms.

Reflexes: prewired responses to stimuli.

Pavlovian (emotional): learning the situation to release prewired actions.

Deliberation: search and evaluate potential consequences.

Procedural (habits): cached action-chain sequences.



ACTION

Central pattern generators...

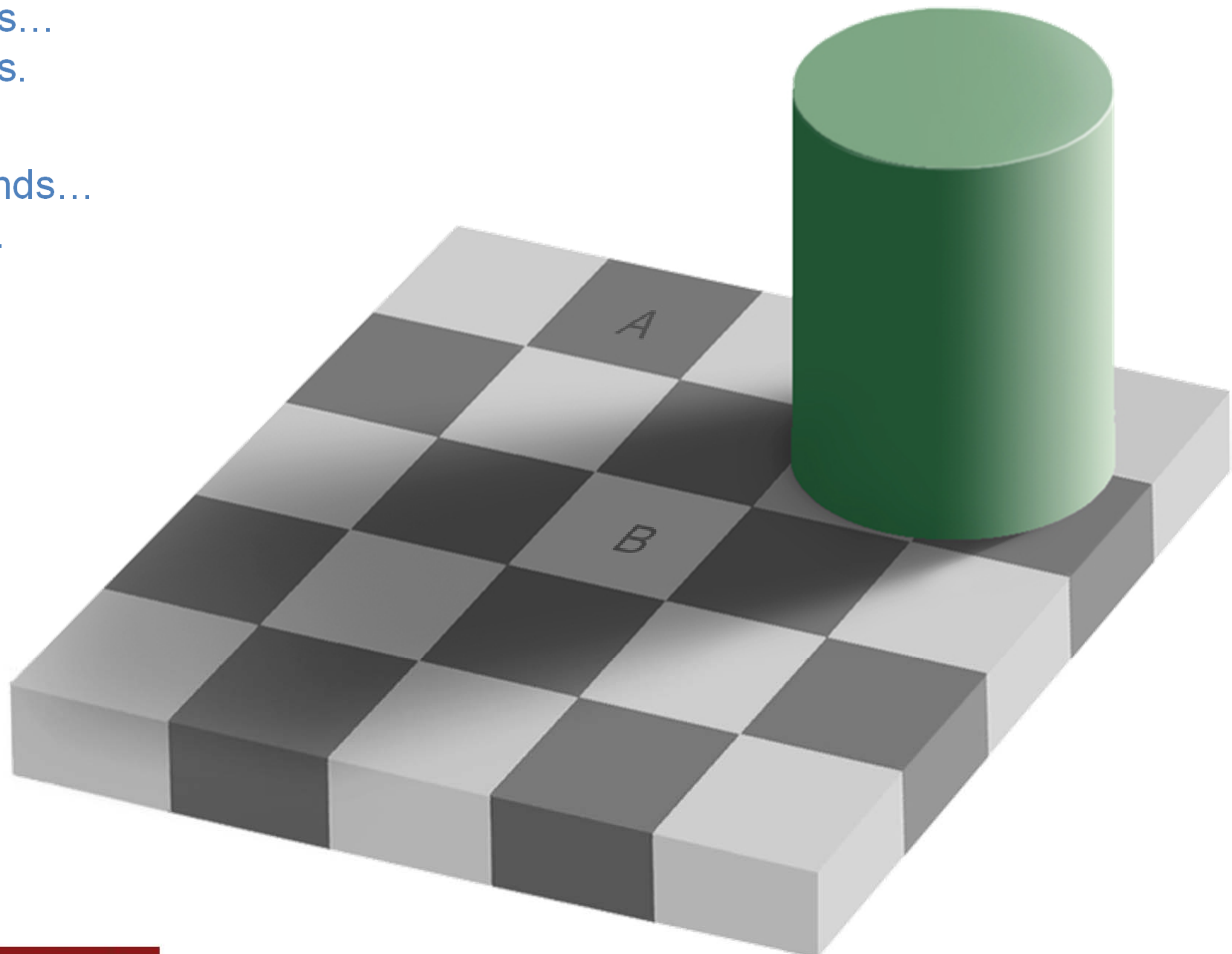
MOTIVATIONAL DESIRES

Reflecting ones current internal (evolutionary) needs and desires.

Situation recognition

We don’t see colors…
we perceive objects.

We don’t hear sounds…
we perceive music.



Environments

Classical rat experiments put rats in “Skinner boxes” with nothing but a lever

But real rats don’t live in these controlled environments.

University of Minnesota

Cue-rich environments

We live in cue-rich environments, and have to **learn** to recognize the key factors of the situation.

This state categorization process defines

… the space that one searches over in planning systems

… the parameters that habit systems respond to.

State of the world as a categorization problem

Note: this is the <u>inferential brain</u> that you’ve been hearing about all week.

In order to use a POMDP, you first need to identify the <u>possible states</u>.

Hypothesis

The world is ever changing.

Hypothesis

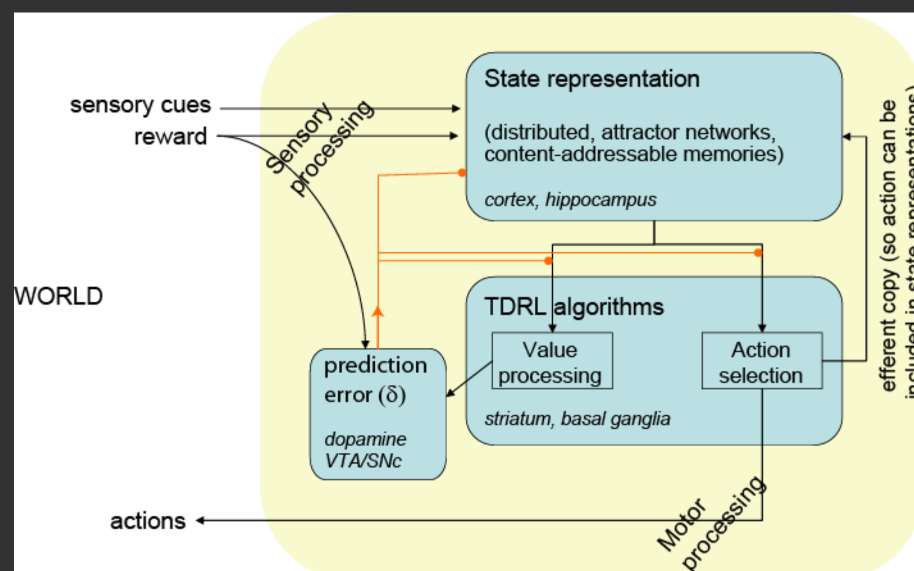
Decisions are made on categorized representations.

Implication

There is a categorization process.

Conclusion

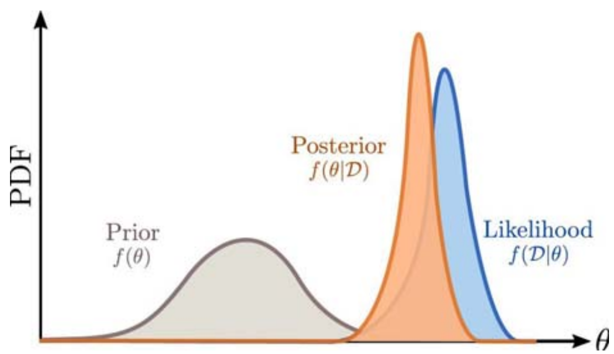
At least part of the addictive process can be caused by mistakes in this categorization process.



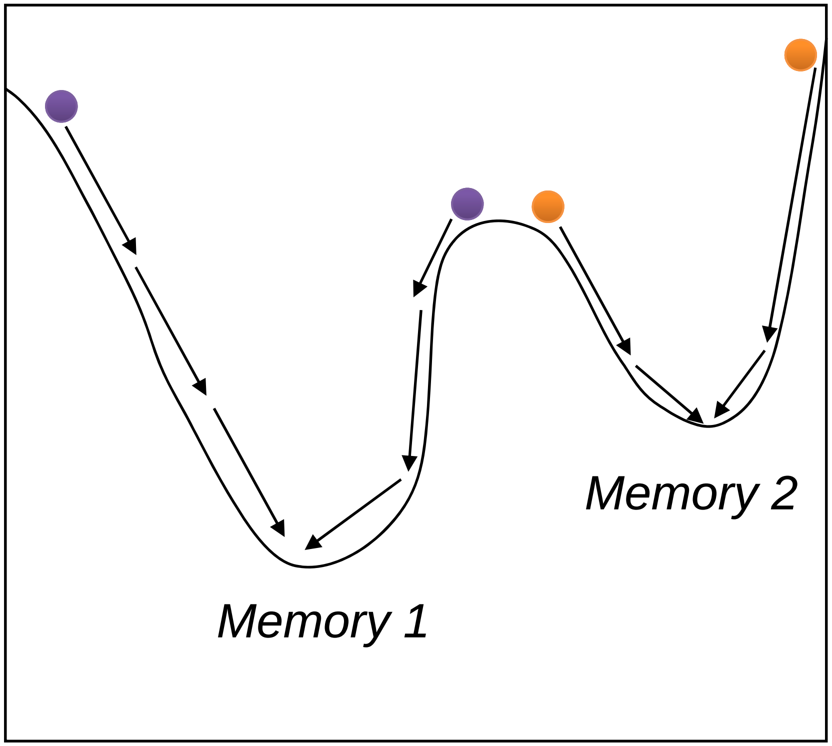
Two theories of categorization

"Failure modes"

Bayesian update



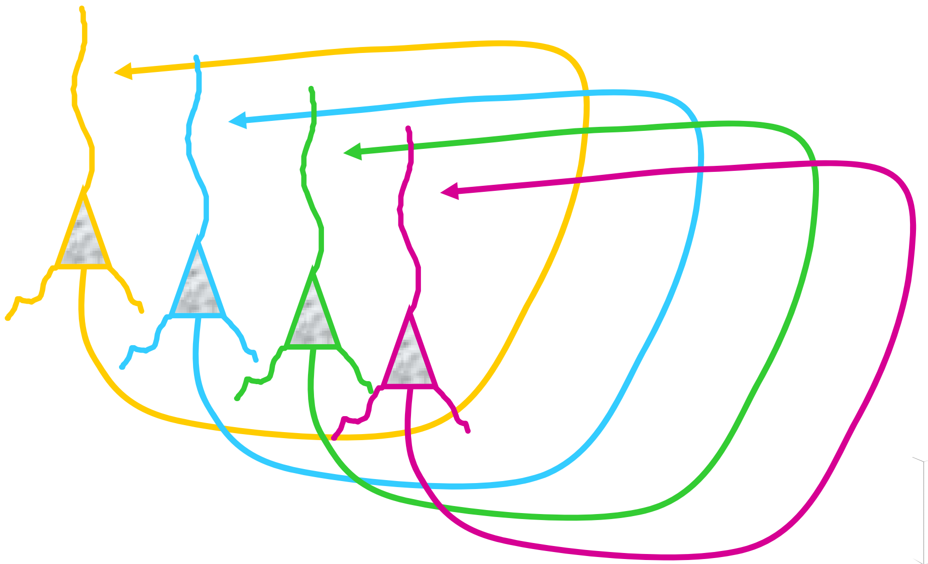
Basins of attraction



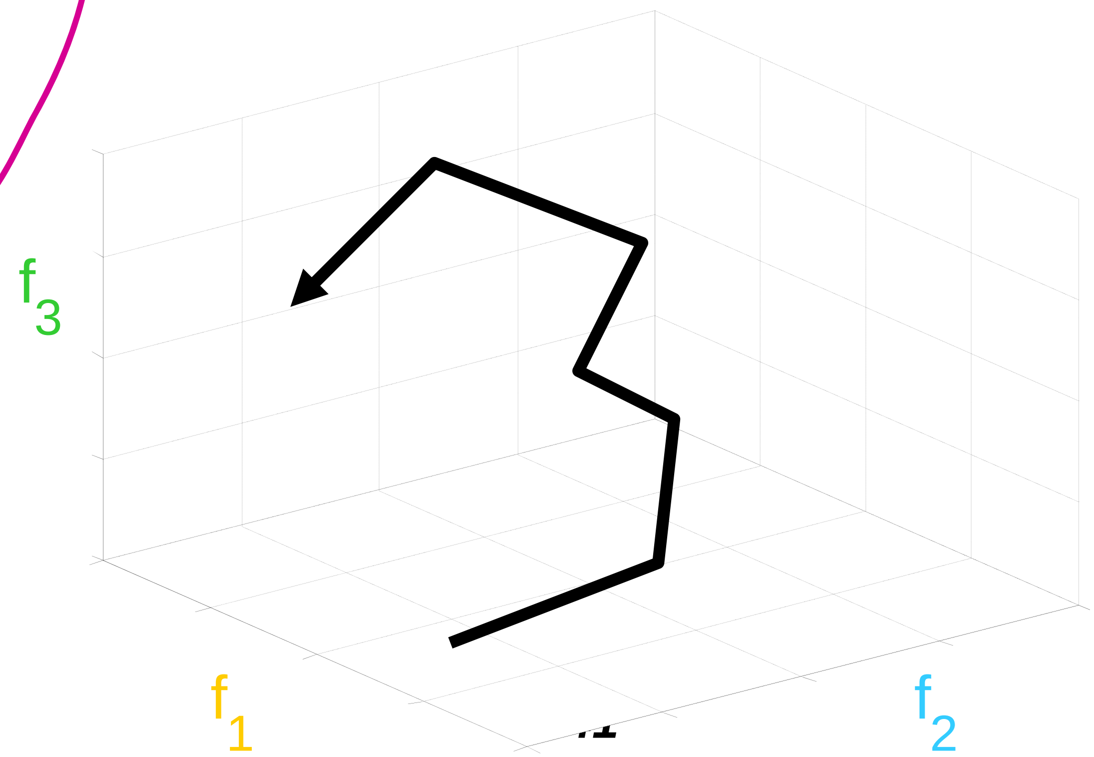
Different sets of neural activity

Cell assemblies as a point in N-dimensional space

"Failure modes"

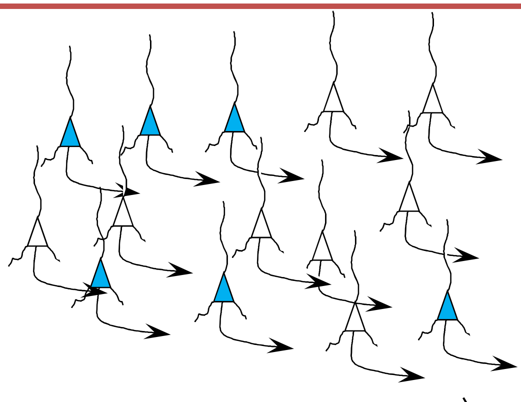


F=(f₁,f₂,f₃,f₄,…fₙ)

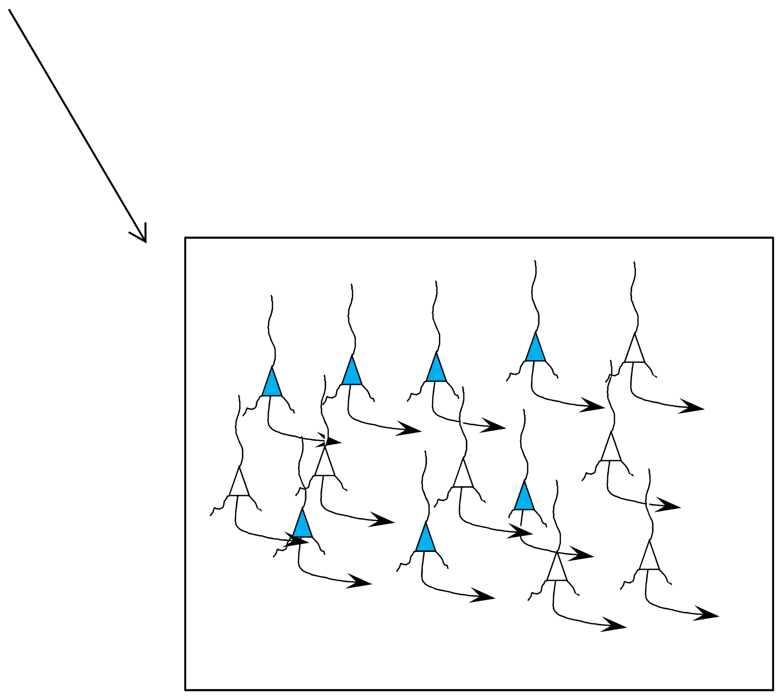


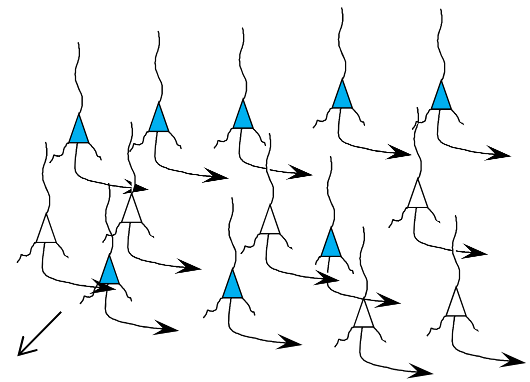
A distance metric

“Failure modes”



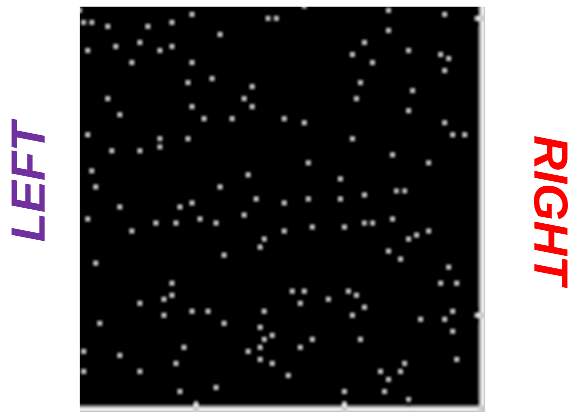
3 cells changed

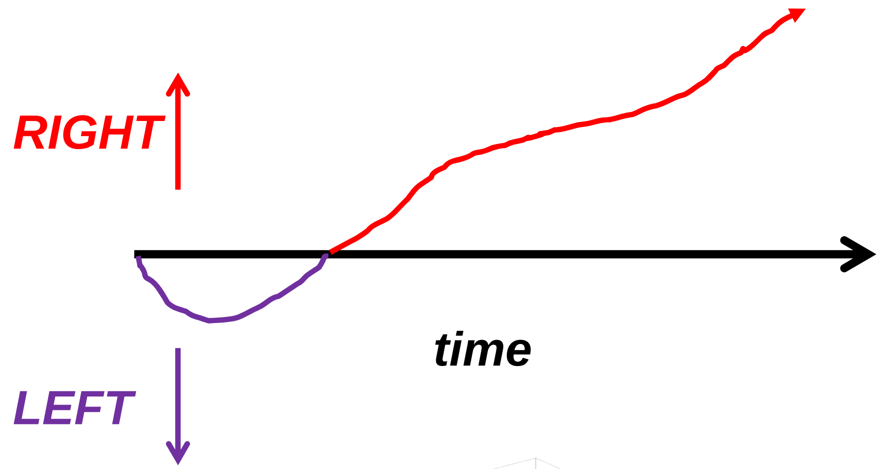


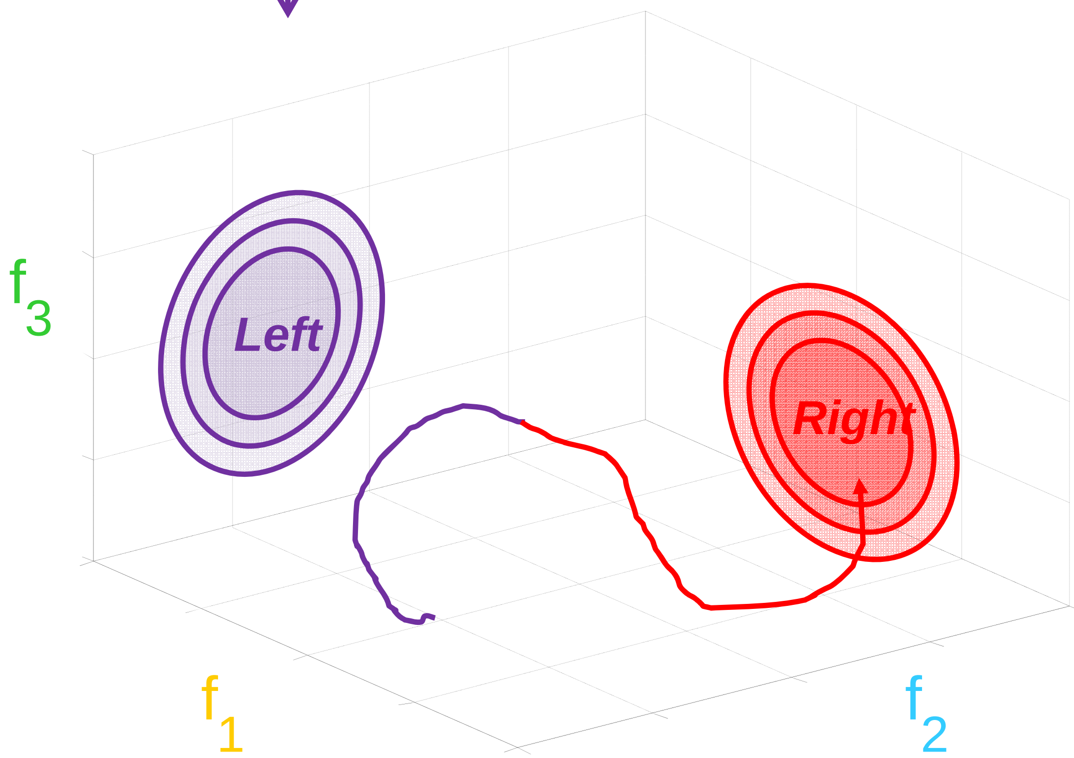


1 cell changed

Basins of attraction







Integrating information ***is*** descent into a **basin of attraction**, by moving through **neural space**.

A starting model

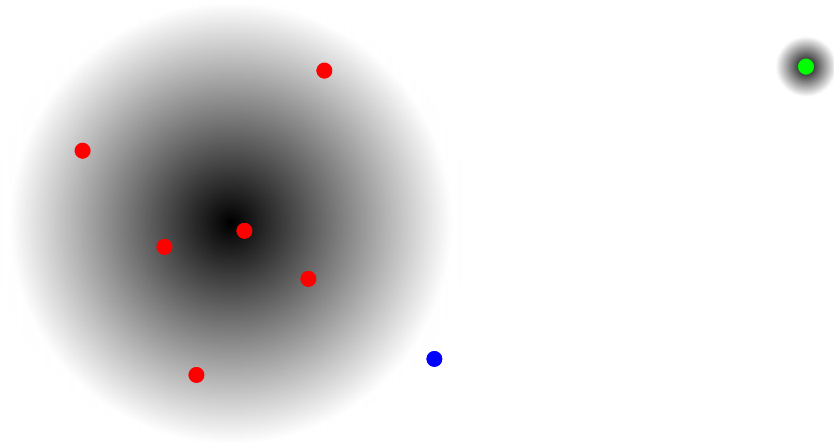
Let's hypothesize that the classification window depends on the level of dopamine present in the system.

That is, the depth of the basin of attraction depends on dopamine.

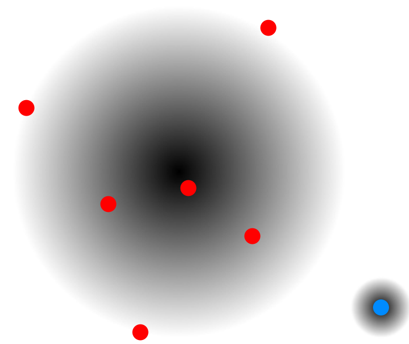
Note that depth of the basin depends on the "inverse temperature" – deep basins are cold (low noise), shallow basins are hot (high noise).

"Failure modes"

High dopamine

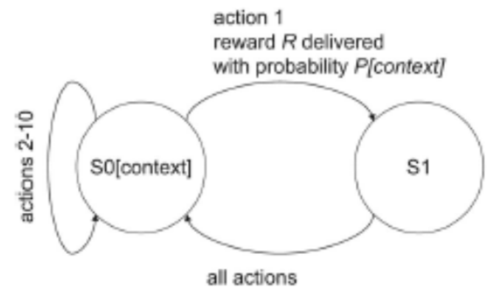


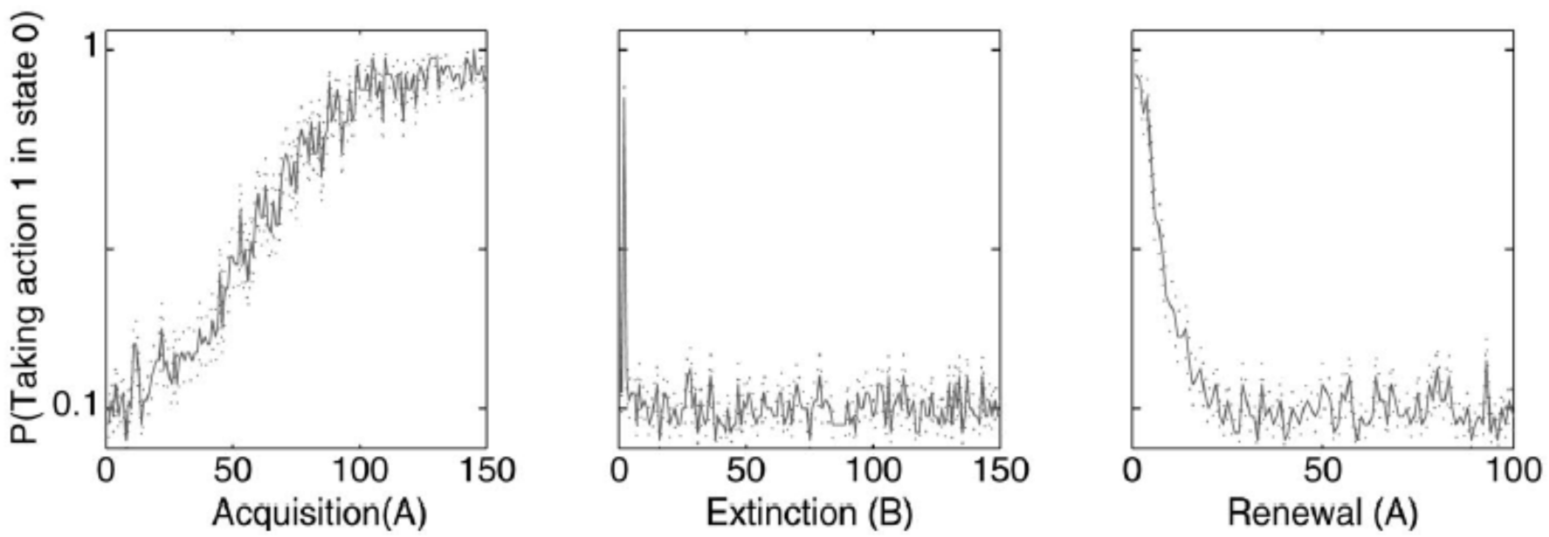
Low dopamine



Behavioral extinction

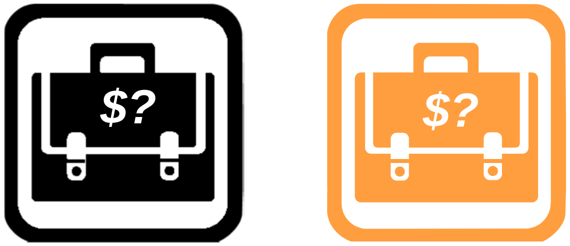
Situation recognition

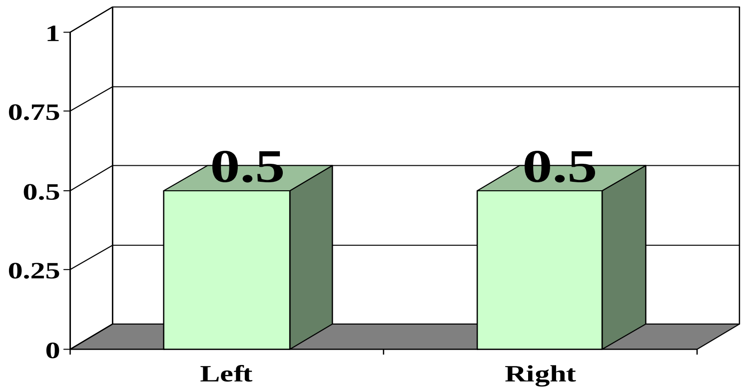




Brains work because information

The computational perspective

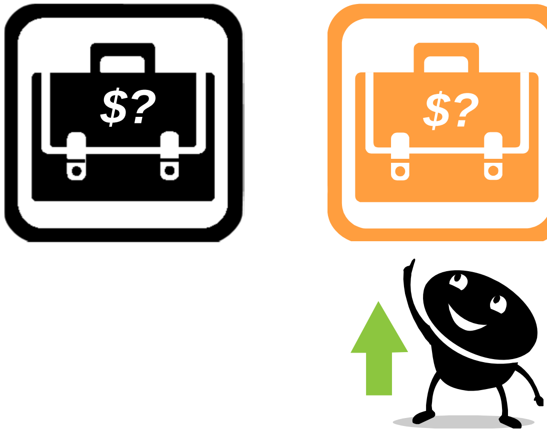


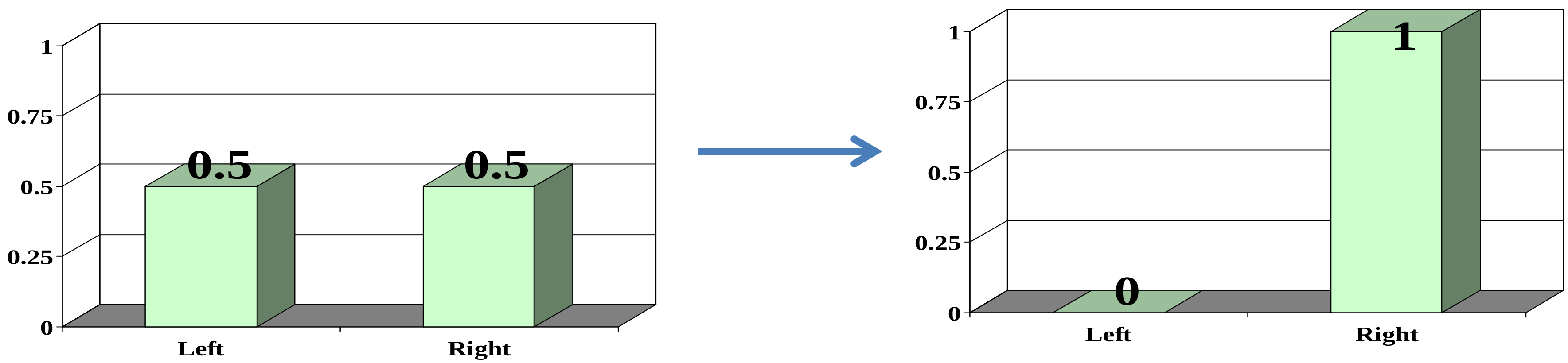


Brains work because information

Even if we can't measure the actual entropy, we can measure the **information gained** (entropy accounted for).

The computational perspective





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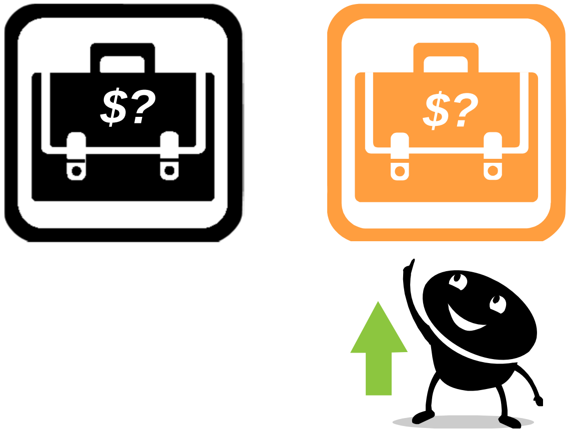
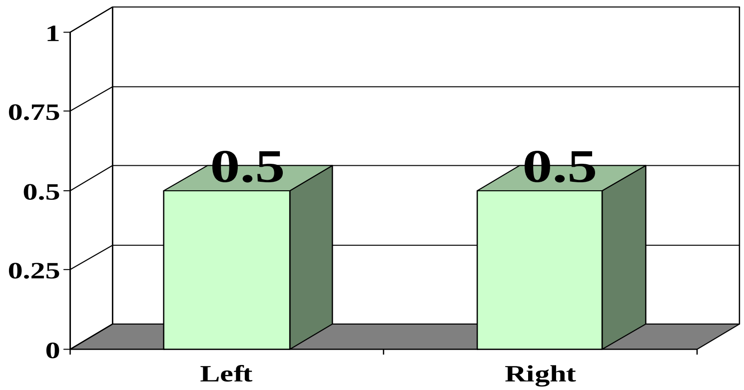
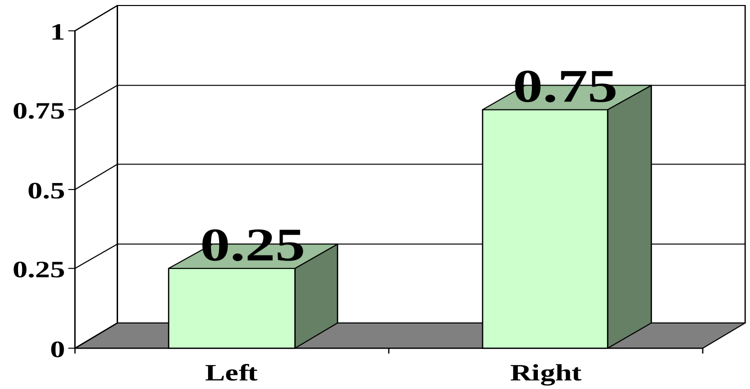




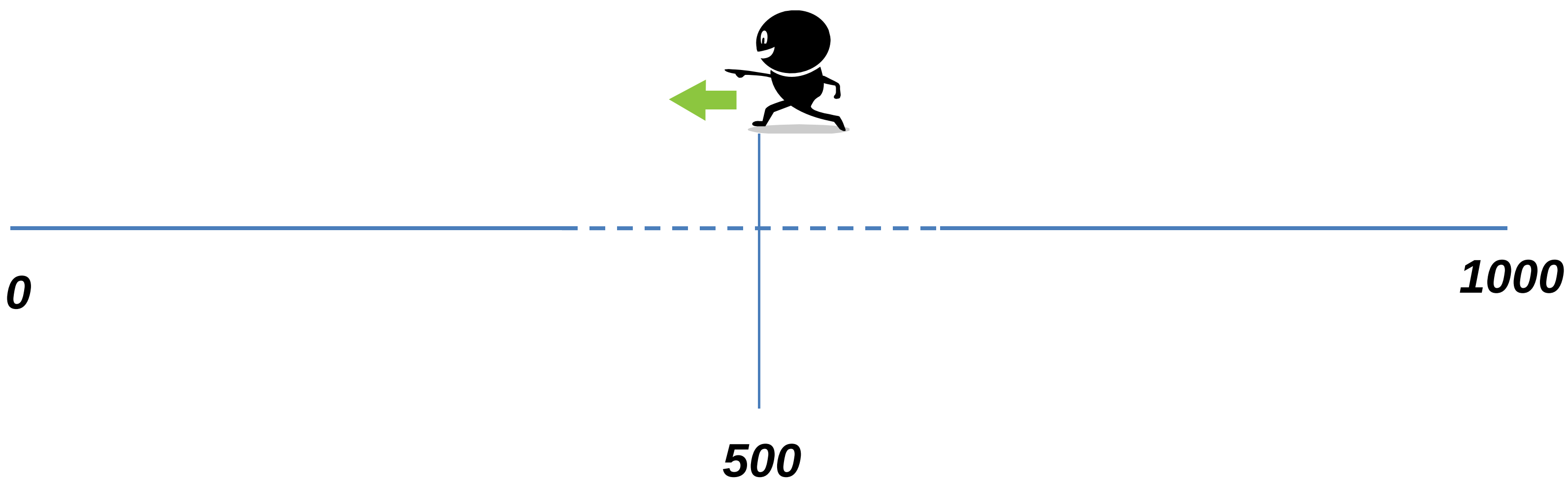


Brains work because information

Even if we can't measure the actual entropy, we can measure the information gained.

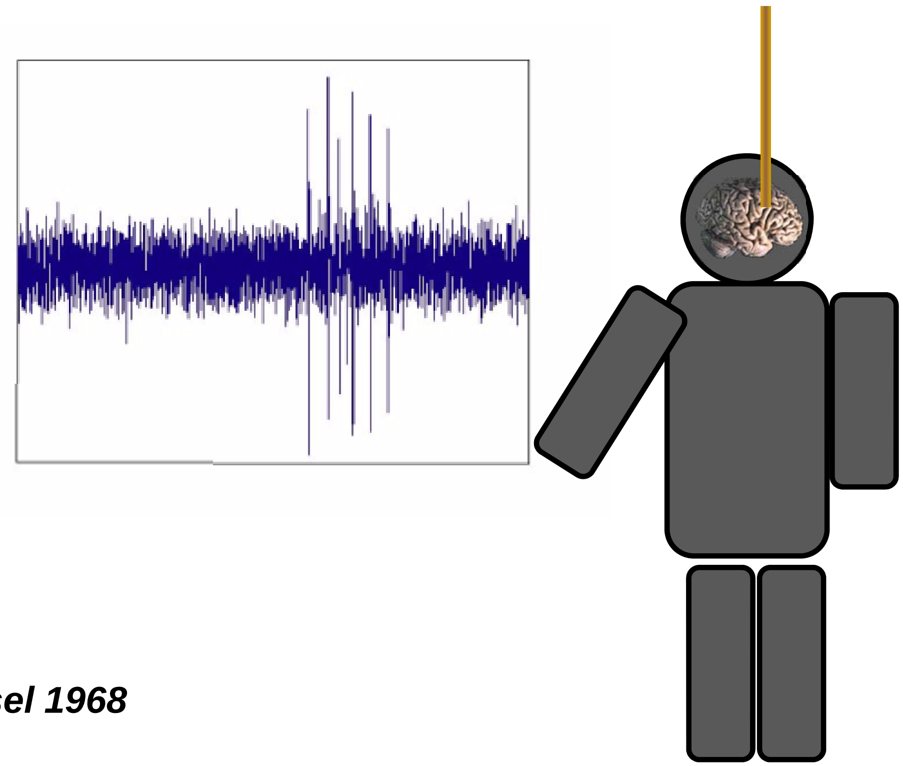
The computational perspective

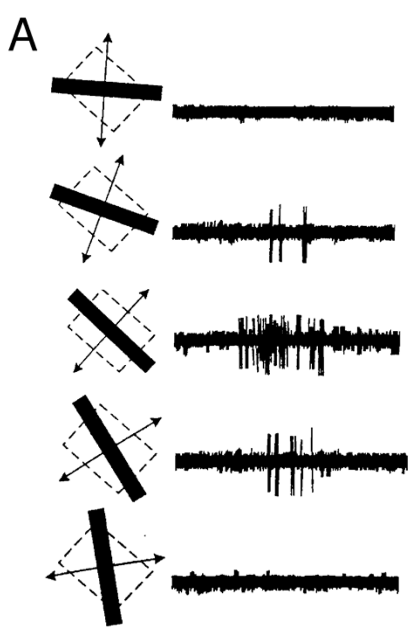
This is called the <u>mutual information</u> between X and Y.



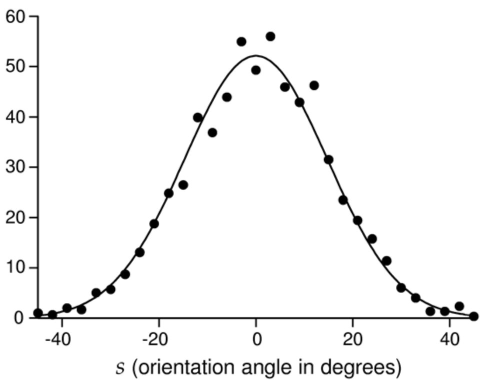
Mutual information

Neural signals have mutual information with properties of the world.



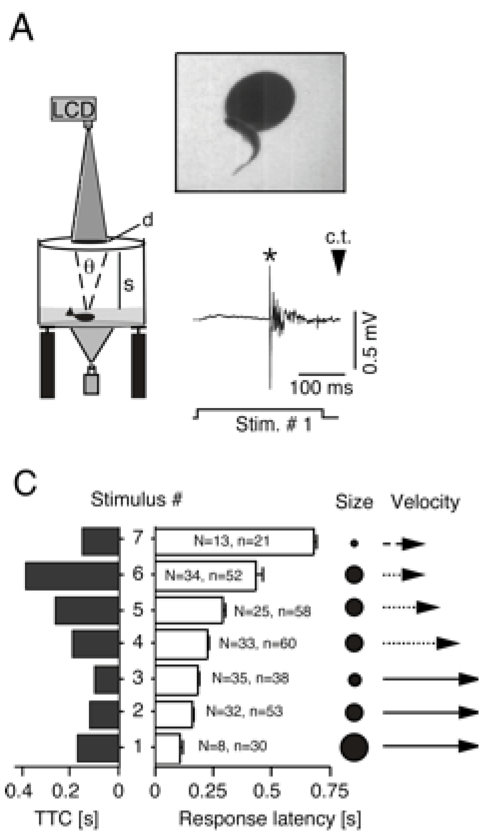


V1 responses
Hubel and Weisel 1968

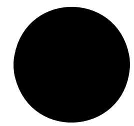


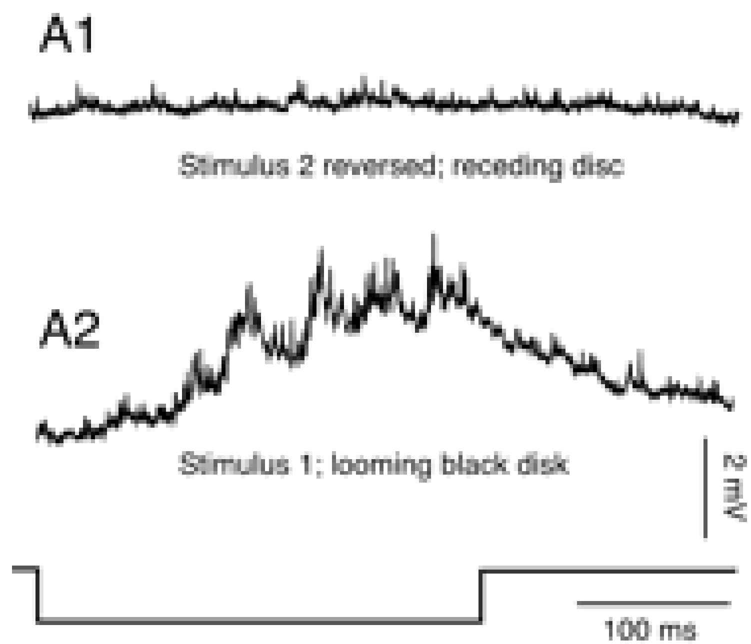
Mutual information

The Mauthner cell in the goldfish.



Preuss…Faber (Jnsci 2006)





The computational perspective

Mutual information

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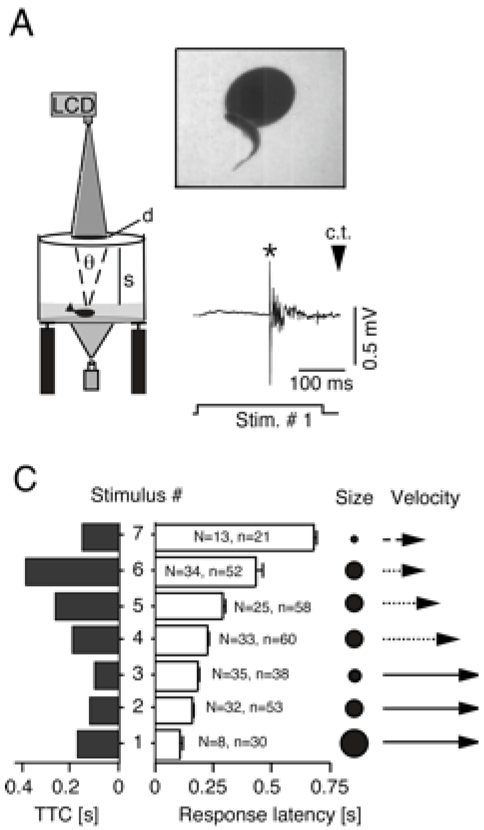


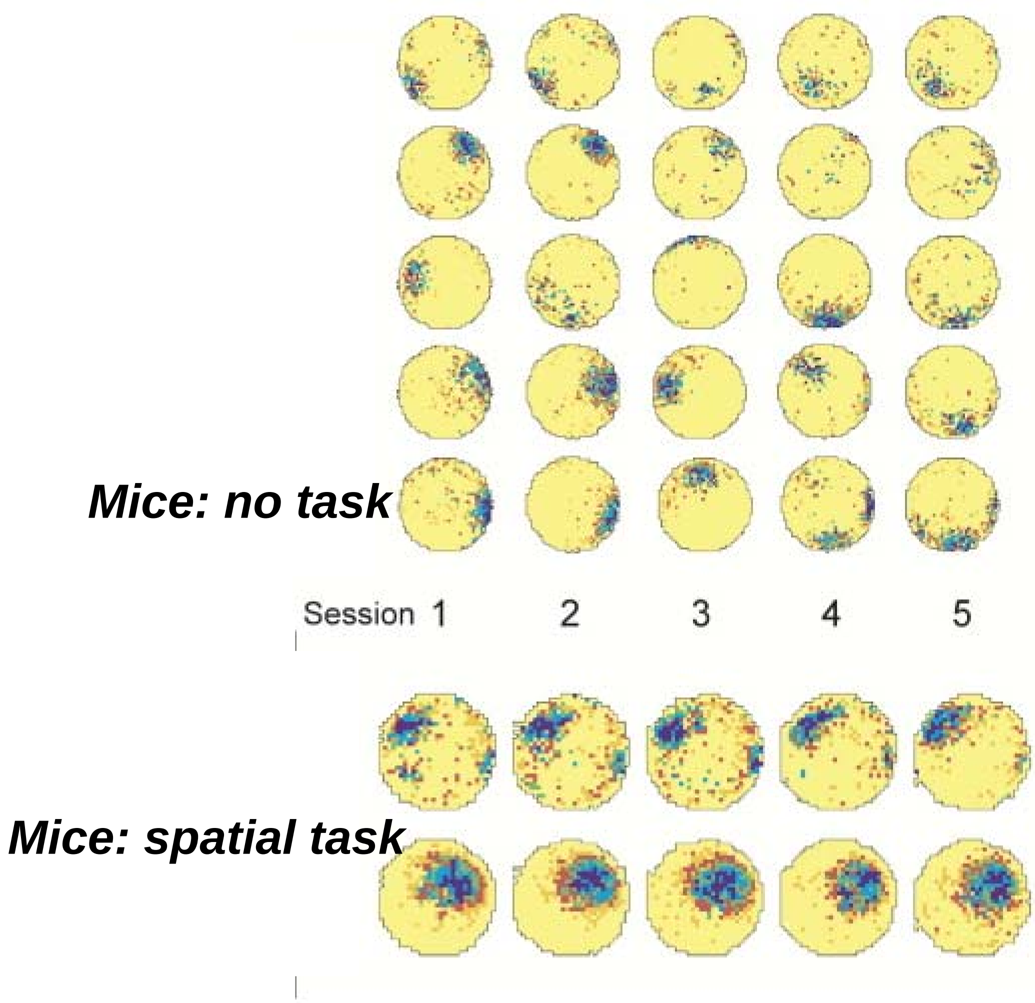
Preuss…Faber (Jnsci 2006)

Tuning curve stability and attention

Place cells are more stable from day to day if the animal is "attending" to a task.

"Failure modes"

Kentros et al. 2004



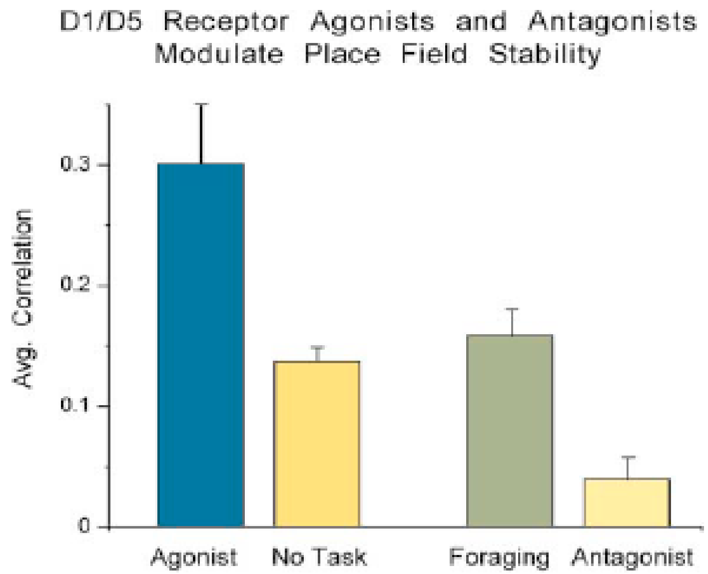
Tuning curve stability = stable categorization = stable basins of attraction.

Tuning curves stability

“Failure modes”

Tonic levels of dopamine control the stability of tuning curves.

In mathematical terms, tonic dopamine strengthens the inertia of the
basin of attraction in the content addressable memory.



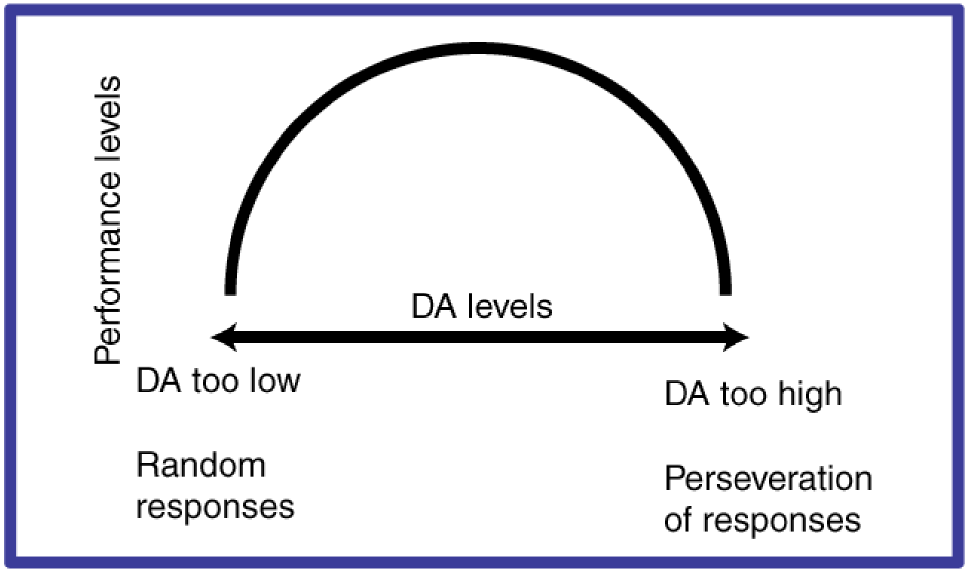
Kentros et al. 2004

Tuning curve stability = stable categorization = stable basins of attraction.

The inverted U dopamine curve

Tonic DA (in prefrontal cortex) controls the perseveration of action choice.

"Failure modes"



After Goldman-Rakic et al., 2000, Seamans and Yang, 2004.

Implications: Problem gambling and the illusion of control

“Failure modes”

Hypothesis

Unexpected gains produce acquisition:
$\delta>0$ => store association

Unexpected losses produce state-splitting:
$\delta<0$ => transform state representation

Implication

A sequence of wins can produce anomalous expectations, that cannot be unlearned from subsequent losses.

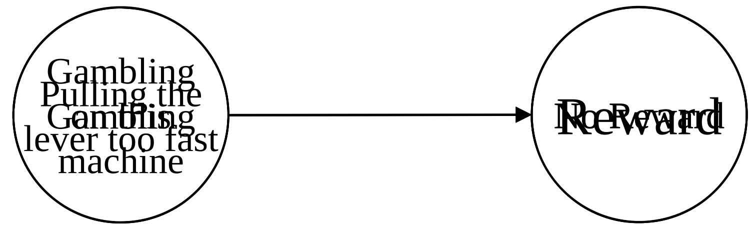
This can explain

Hindsight bias in which losses are "explained away" (as a difference between s and s').

The illusion of control in which gamblers believe they can control statistical situations (by moving the state from s' to s).

The path to problem gambling which begins with a statistically unlikely sequence of wins.

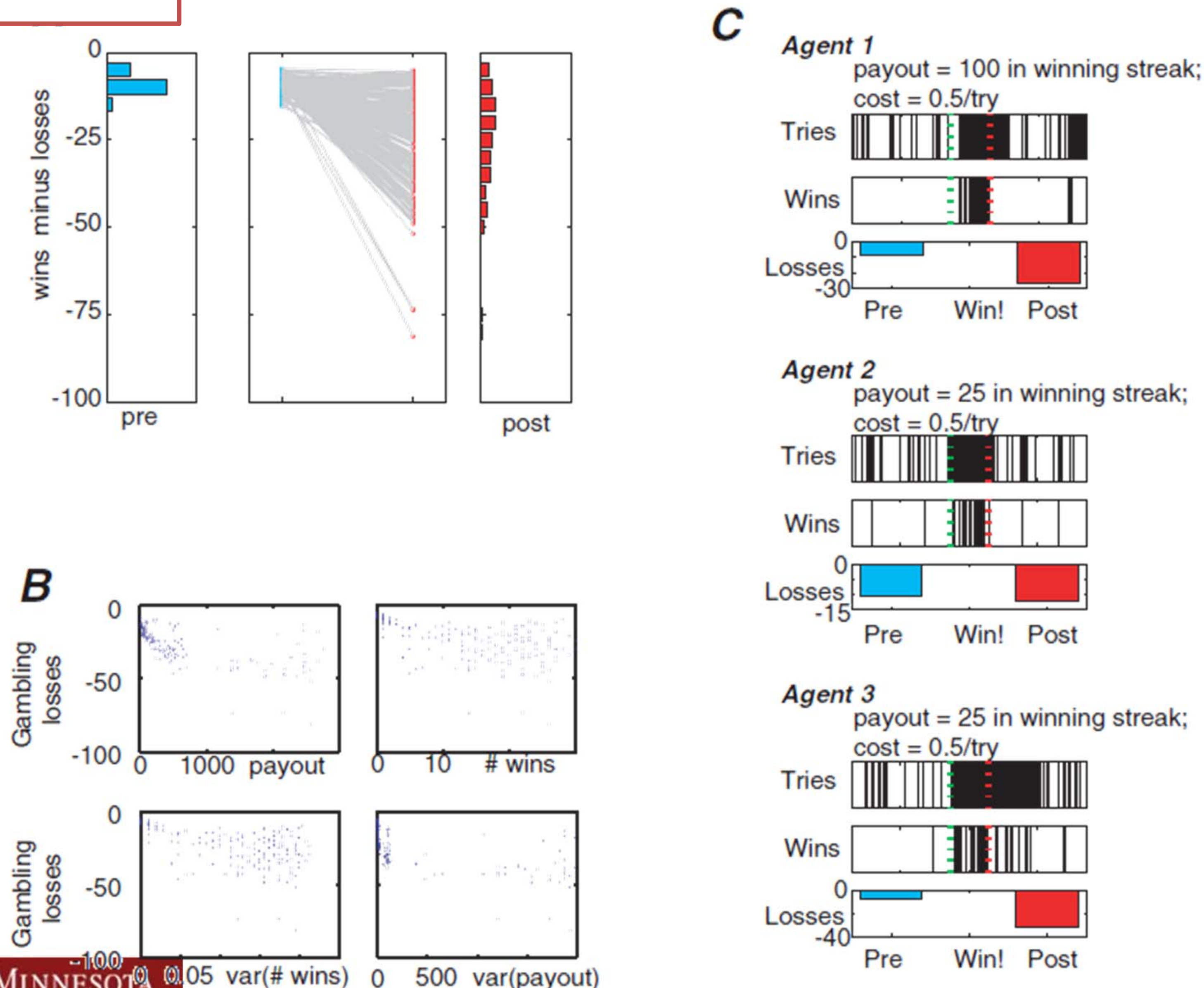
Langer and Roth, 1975. Custer, 1984. Wagenaar, 1988. Elster, 1999.



- Slot machines have gotten more complex, not less. Near misses drives one to find new ways to interpret problems.

Simulations of problem gambling

"Failure modes"



Implications for treatment

State spaces matter … precommitment

frontiers in BEHAVIORAL NEUROSCIENCE
ORIGINAL RESEARCH ARTICLE
published: 13 December 2010
doi: 10.3389/fnbeh.2010.00184

A reinforcement learning model of precommitment in decision making

*Zeb Kurth-Nelson and A. David Redish**

frontiers in NEUROSCIENCE
FOCUSED REVIEW
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Don't let me do that! – models of precommitment

Zeb Kurth-Nelson[1] and A. David Redish[2]*

Contingency management

frontiers in Psychiatry
HYPOTHESIS AND THEORY
published: 01 June 2015
doi: 10.3389/fpsyt.2015.00076

Contingency management and deliberative decision-making processes

Paul S. Regier[1†] and A. David Redish[2]*

Precommitment

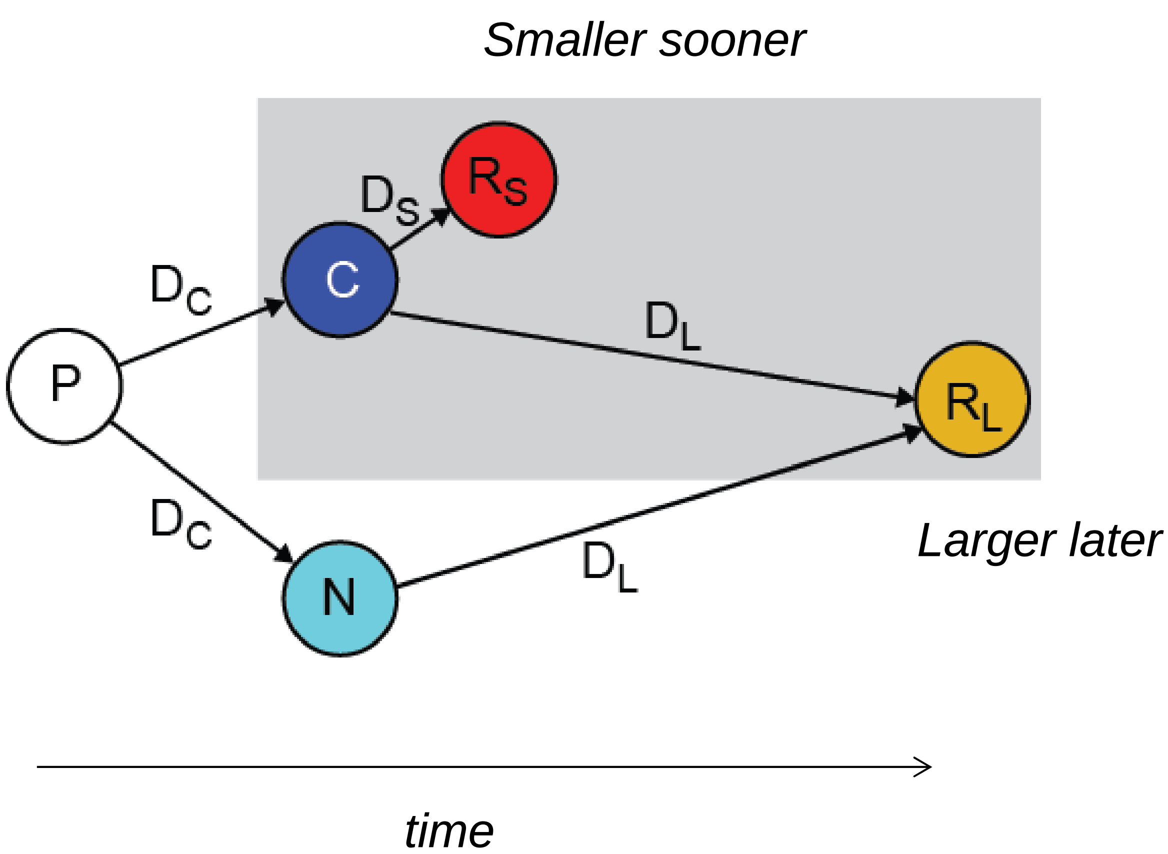
Implications for treatment

Zeb Kurth-Nelson, Redish (2010) Frontiers in Behav Nsci
Zeb Kurth-Nelson, Redish (2012) Frontiers in Nsci

Precommitment entails rejecting a future choice to prevent an action.

This means the system has to prefer $R_S \succcurlyeq R_L$ but also to prefer $N \succcurlyeq C$,

which means
$R_S \succcurlyeq R_L$ at $T_{C/N}$
but also
$R_S \preccurlyeq R_L$ at P

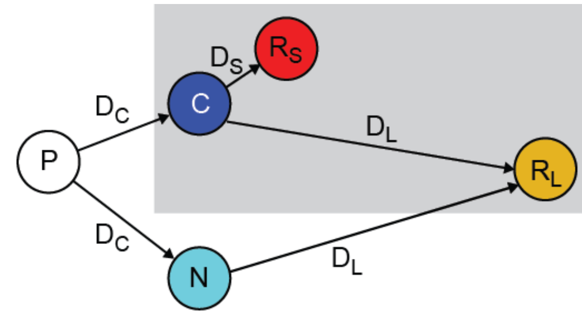


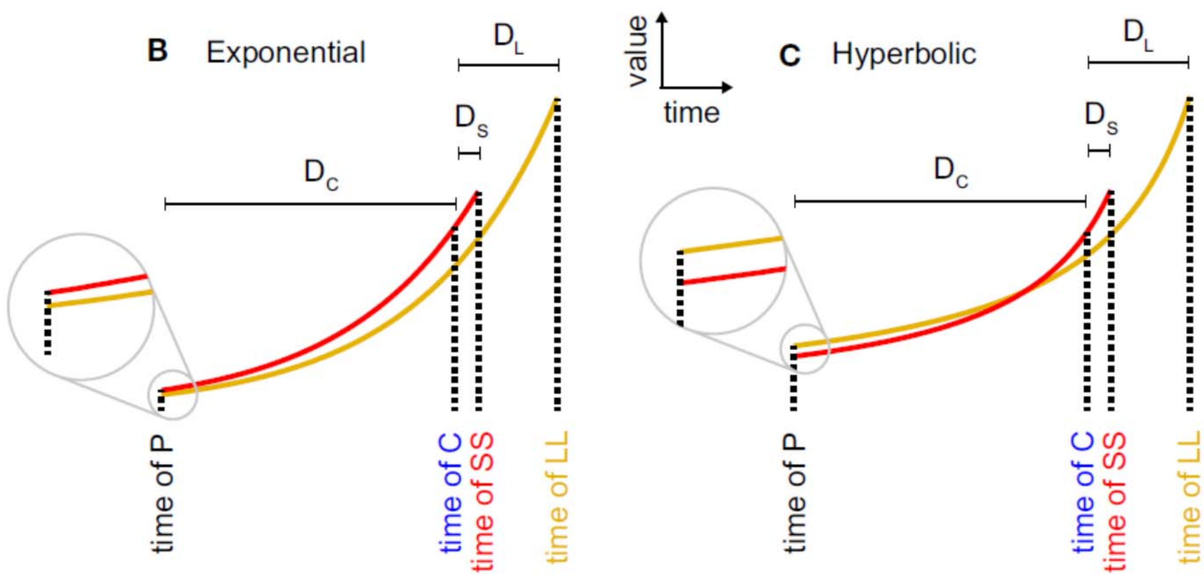
Precommitment

Implications for treatment

Zeb Kurth-Nelson, Redish (2010) Frontiers in Behav Nsci
Zeb Kurth-Nelson, Redish (2012) Frontiers in Nsci

Precommitment arises from non-exponential discounting functions.





Precommitment

Implications for treatment

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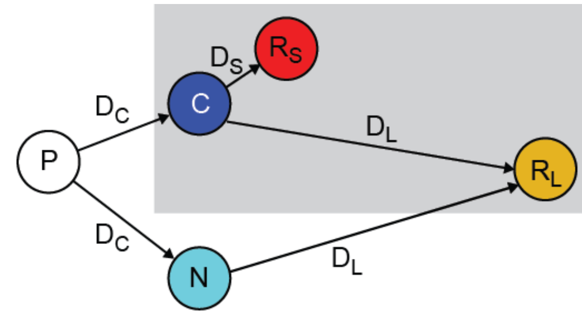
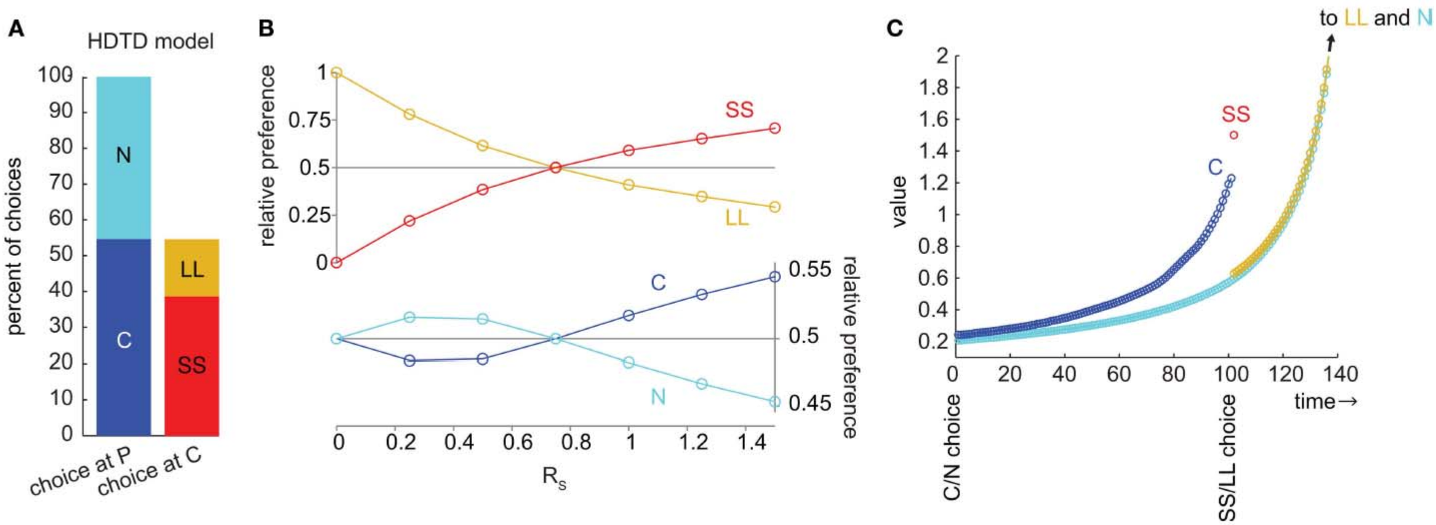
Zeb Kurth-Nelson, Redish (2012) Frontiers in Nsci

But hyperbolic discounting is not enough.





Semi-markov model with hyperbolic discounting.

Precommitment

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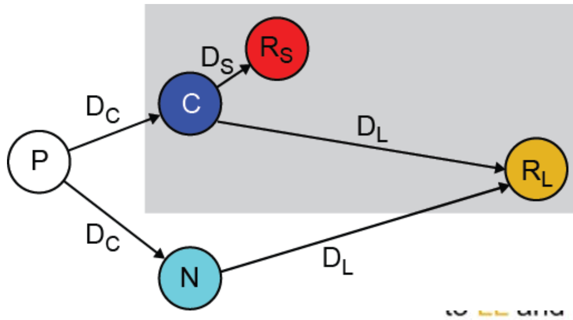

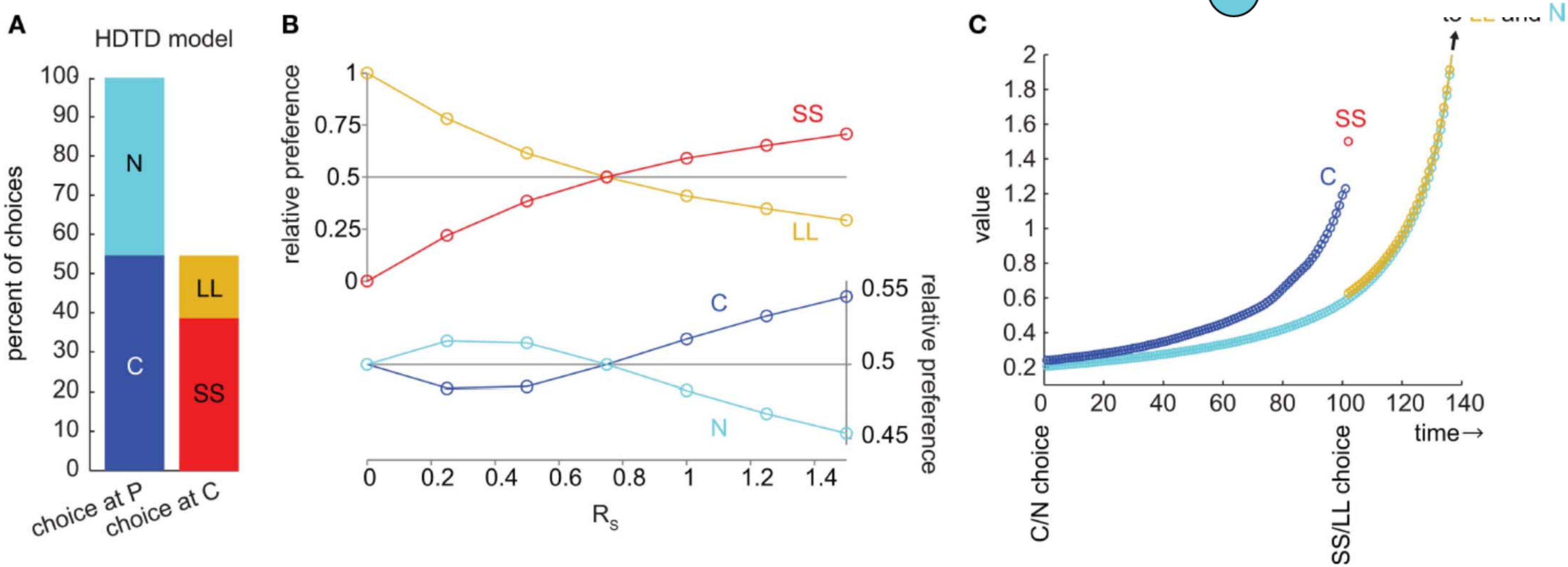

HDTD model (Alexander and Josh Brown 2010).

Precommitment

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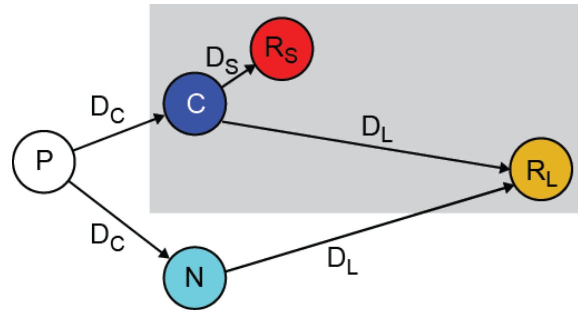
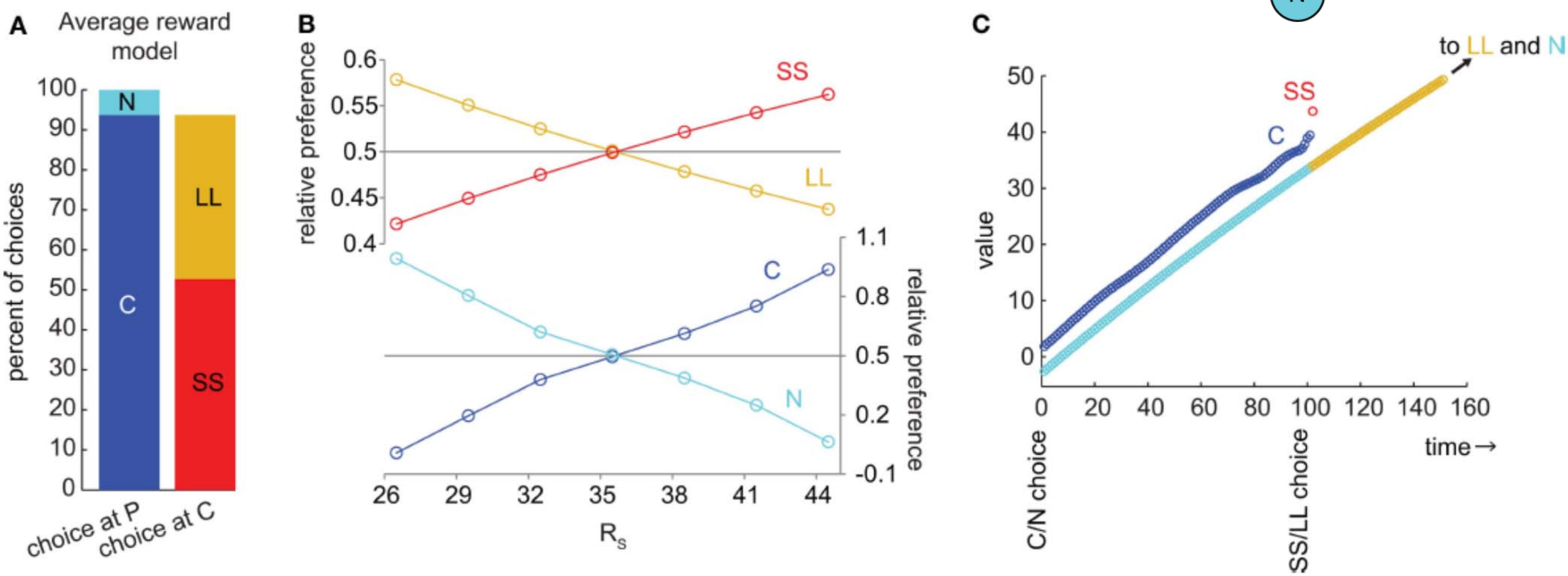




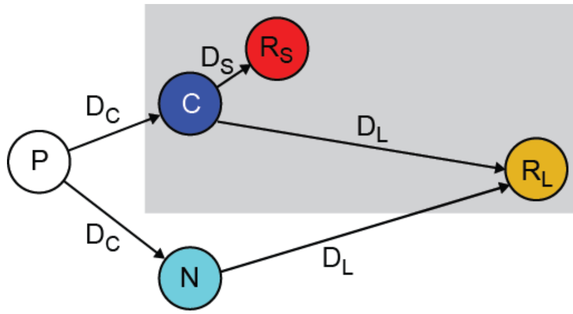
Average reward (hyperbolic) model (Daw and Touretzky 2000).

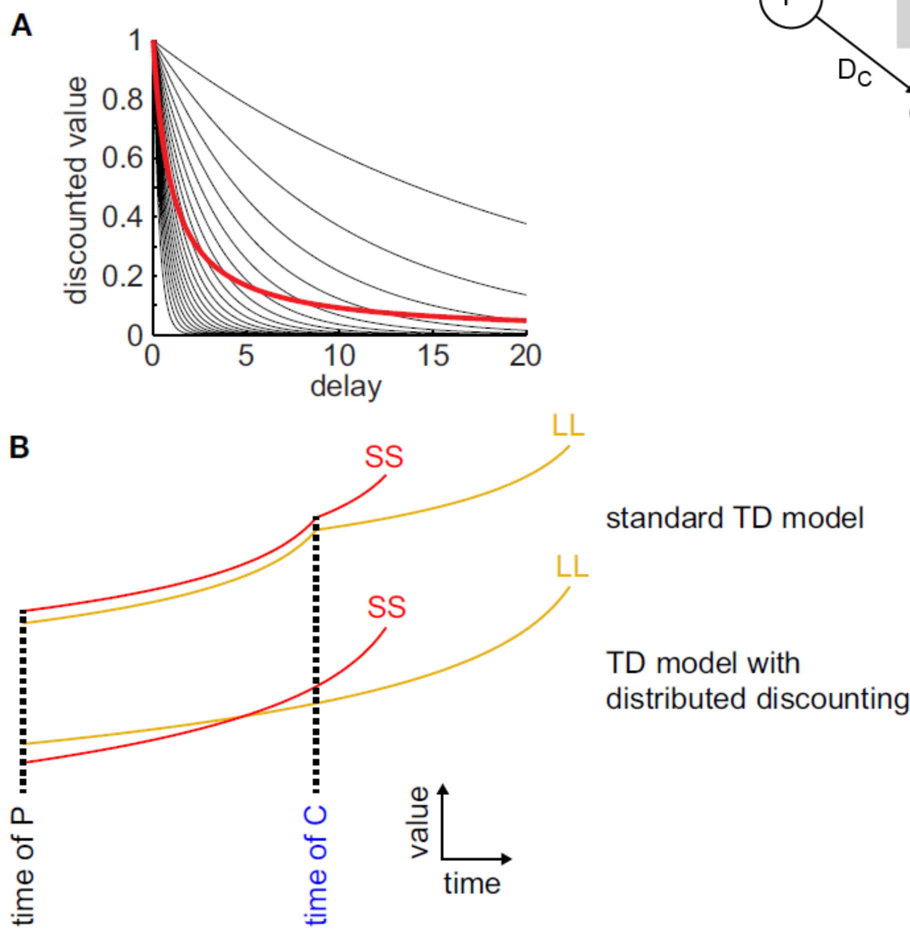
Precommitment

Implications for treatment

Zeb Kurth-Nelson, Redish (2010) Frontiers in Behav Nsci
Zeb Kurth-Nelson, Redish (2012) Frontiers in Nsci

Precommitment requires crossing value functions.





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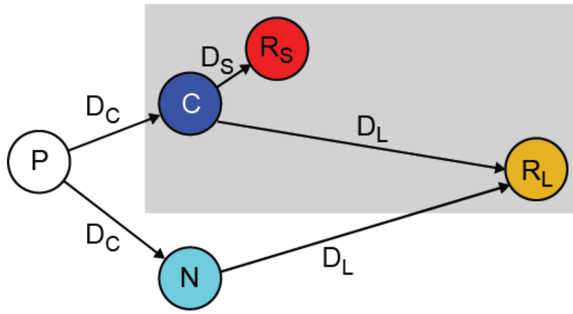
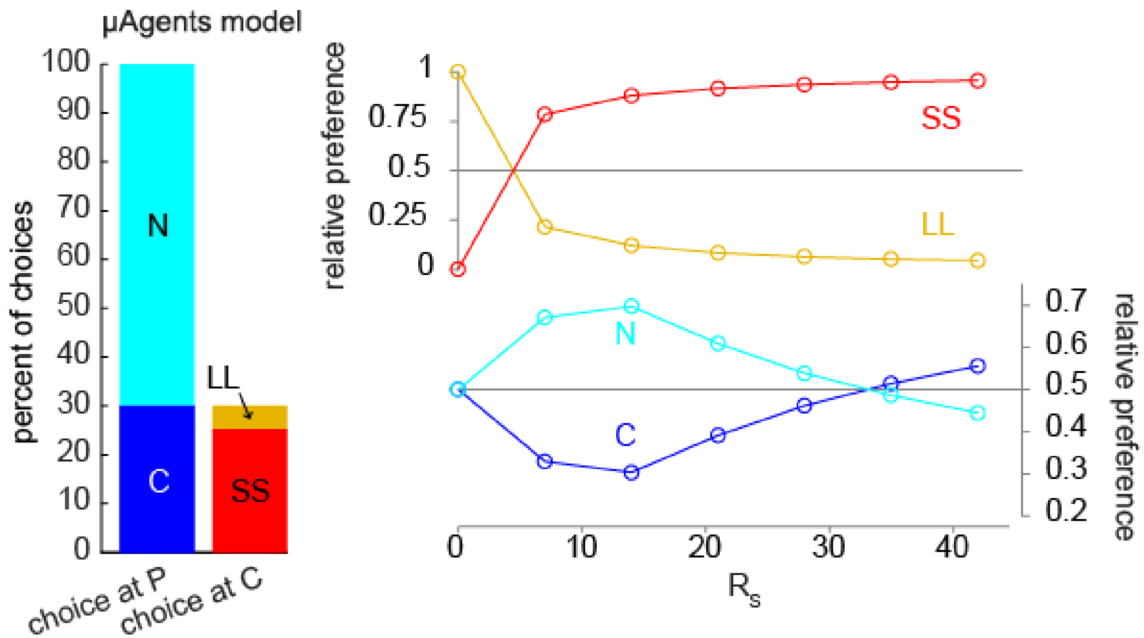


Precommitment depends on having multiple value functions.

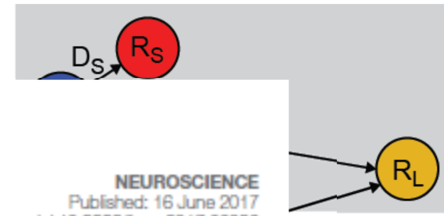


Precommitment

Implications for treatment

Zeb Kurth-Nelson, Redish (2017) Frontiers for young minds

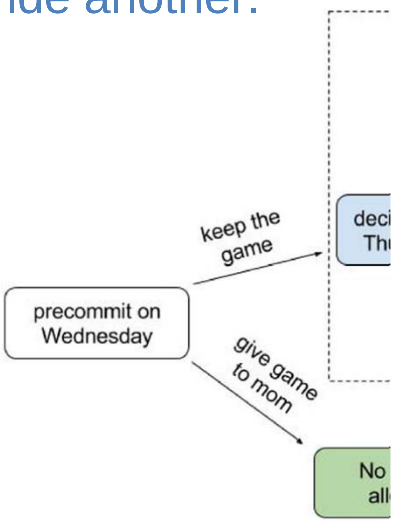
Precommitment is a tool through which one decision system can override another.



NEUROSCIENCE
Published: 16 June 2017
doi: 10.3389/frym.2017.00026

PRECOMMITMENT: A WAY AROUND TEMPTATION

Zeb Kurth-Nelson[1,2] *and A. David Redish*[3*]



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Contingency management and deliberative decision-making processes

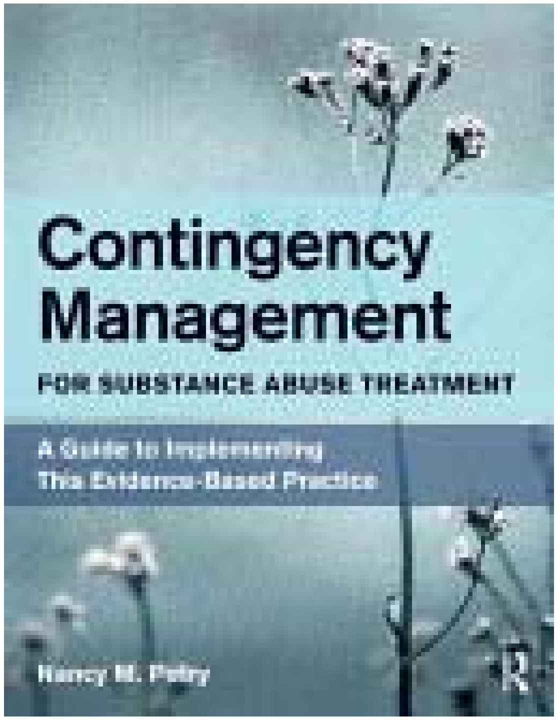
Paul S. Regier[1†] and A. David Redish[2]*

Nudging behavior

Implications for treatment

Paul Regier, Redish (2015) *Frontiers in Psychiatry*

If you don’t use drugs for a week (come in clean), then you receive a small reward.



Current theory:

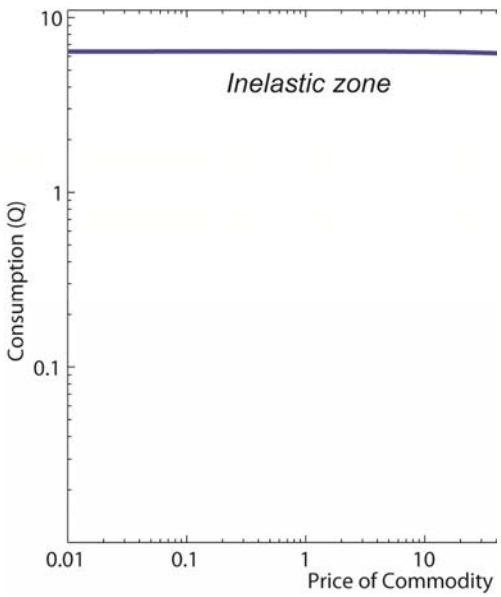
- The reward is an ***alternate reinforcer***.
- Losing it increases the ***opportunity costs*** of the drug.

But the rewards are small.

Increasing the cost of the drug on the street by that amount has little to no effect.

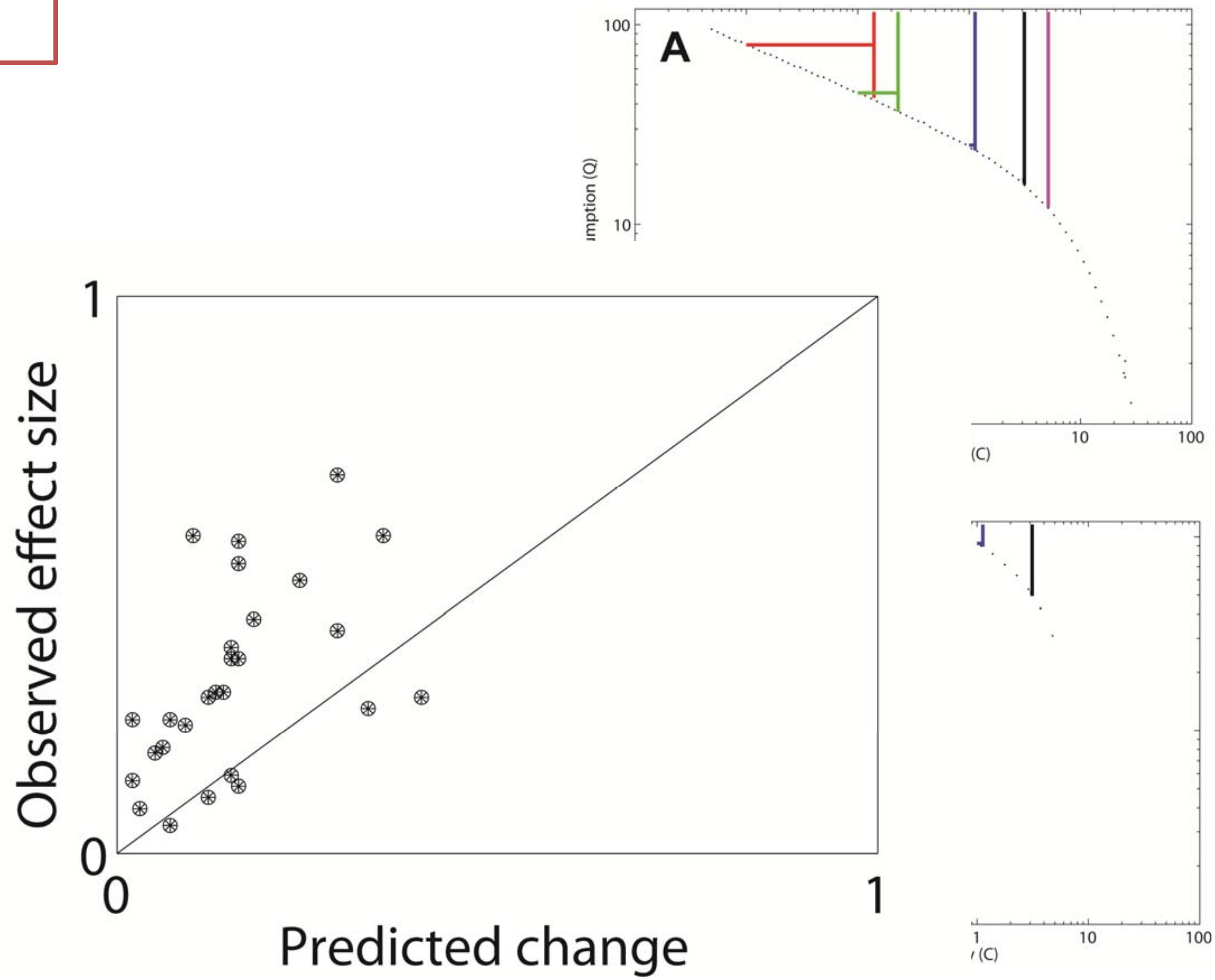
Contingency management works too well

We measured the demand curves from a typical study and compared them to the effects of contingency management.



Implications for treatment

Paul Regier, Redish (2015) *Frontiers in Psychiatry*



Nudging behavior

Implications for treatment

Paul Regier, Redish (2015) *Frontiers in Psychiatry*

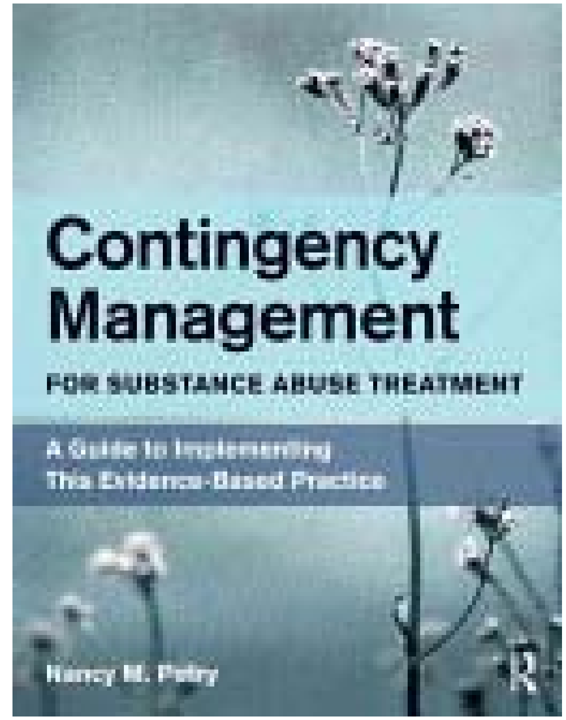
If you don't use drugs for a week (come in clean), then you receive a small reward.

Is it worth it?

Which one?

CM will depend on ***working memory.***

CM will depend on ***prefrontal cortex and hippocampus.***



How can we strengthen deliberation?

We can test for prefrontal-hippocampal integrity.

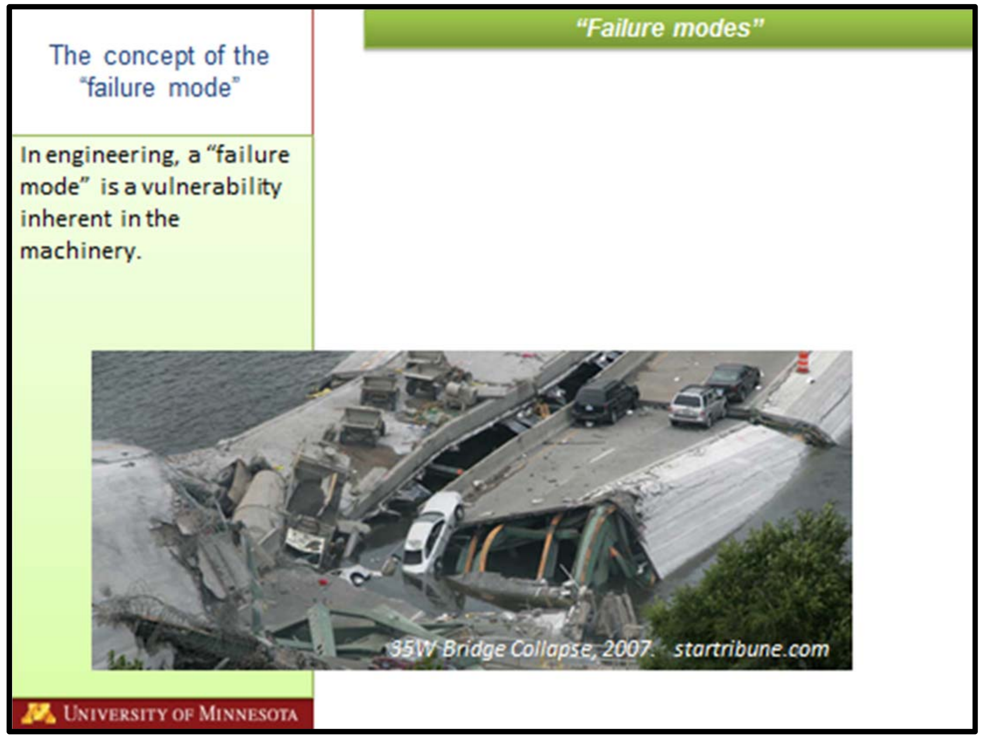
We can train working memory.

We can make the second option more concrete.

We can provide reminders.

Review

We started with a discussion of failure modes…



Review

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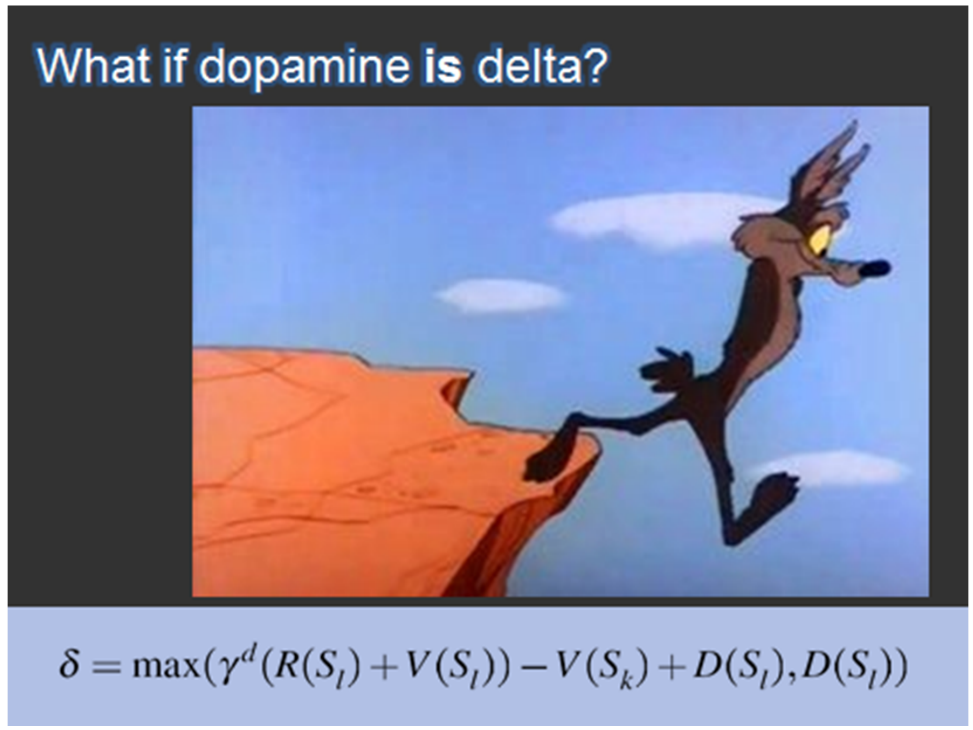

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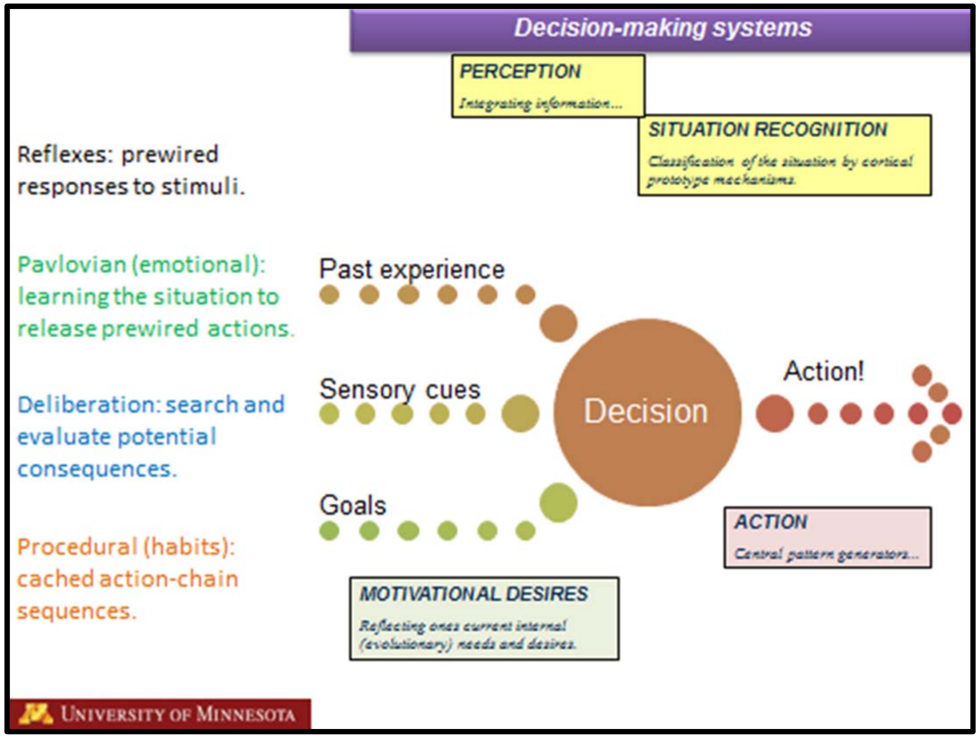
We looked at failure modes across the decision-making system



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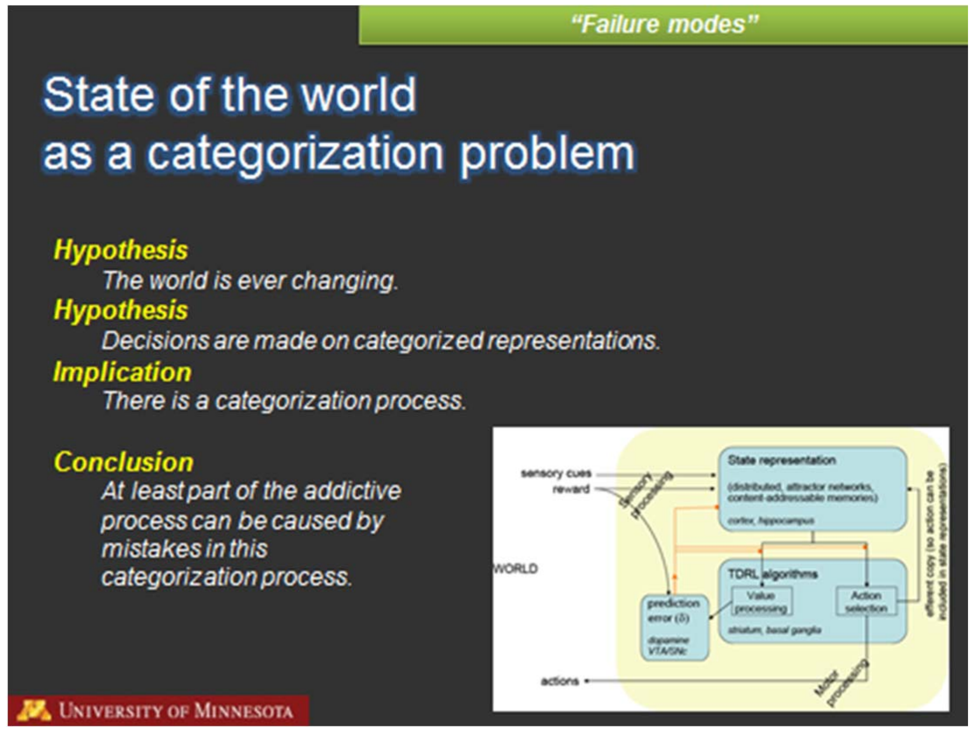

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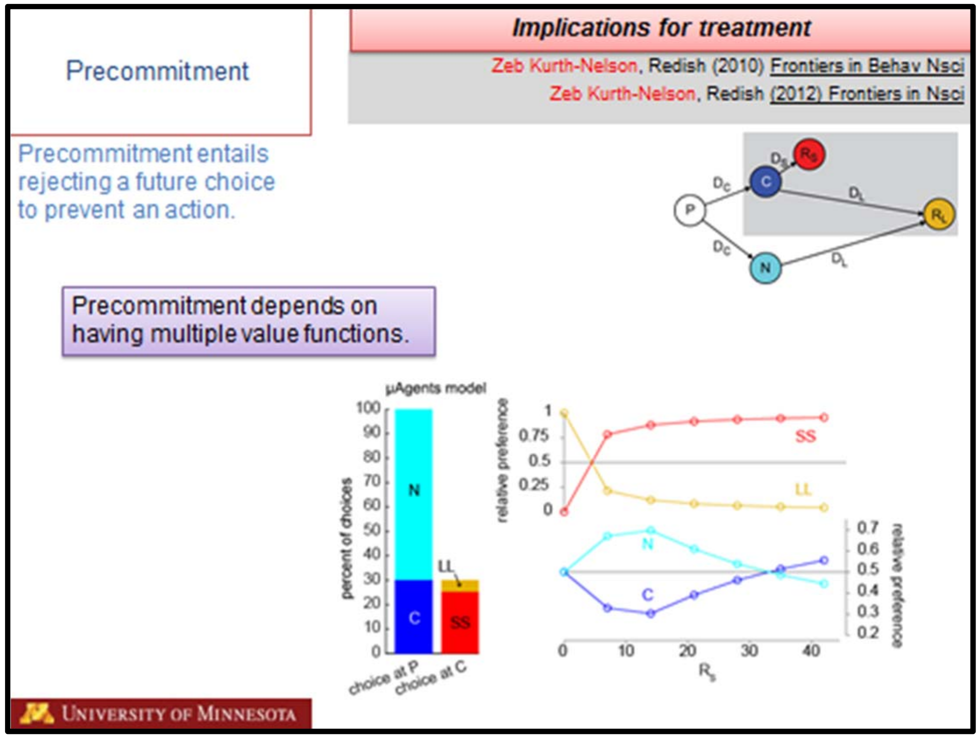

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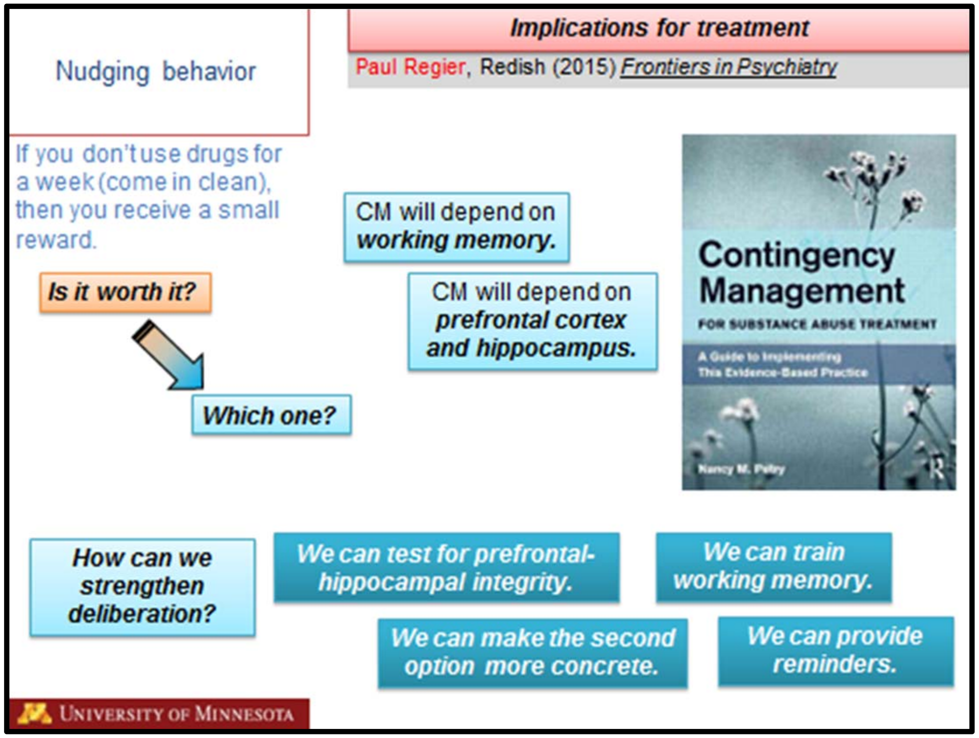
- and did a deep dive into situation recognition.

And ended with implications for treatment

- including a dive into precommitment
- and into contingency management.



Computational psychiatry

taking an engineer's view

To all students in the program:

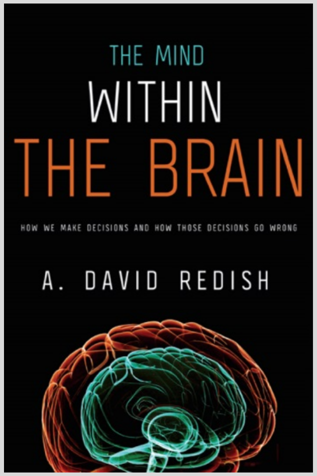
1. *All of our papers are available on the laboratory website redishlab.neuroscience.umn.edu*

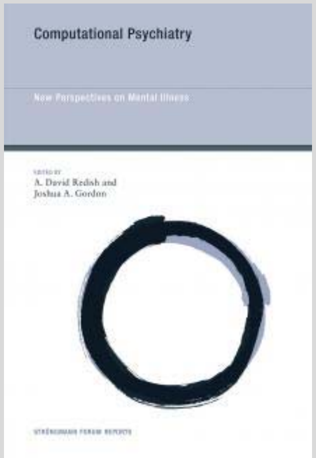
2. *Those of you interested in the "decision making" story, the story is told with extensive citations in the* <u>Mind within the Brain</u> *book.*

3. *We didn't talk about it, but I also recommend the report from the Strungmann Forum with excellent papers by a number of researchers,* ***including both our hosts****.*

4. *Finally, I am currently* ***looking for postdocs****, particularly people who want to work at the boundary between computation and experiment.*

5. *Feel free to send me email with any questions or discussions redish@umn.edu*





Computational models of addiction

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