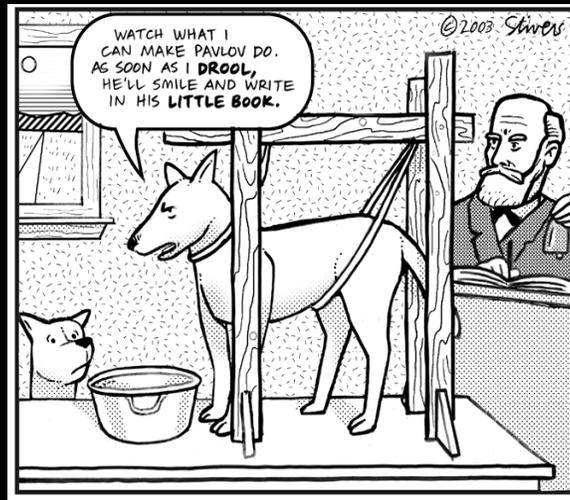
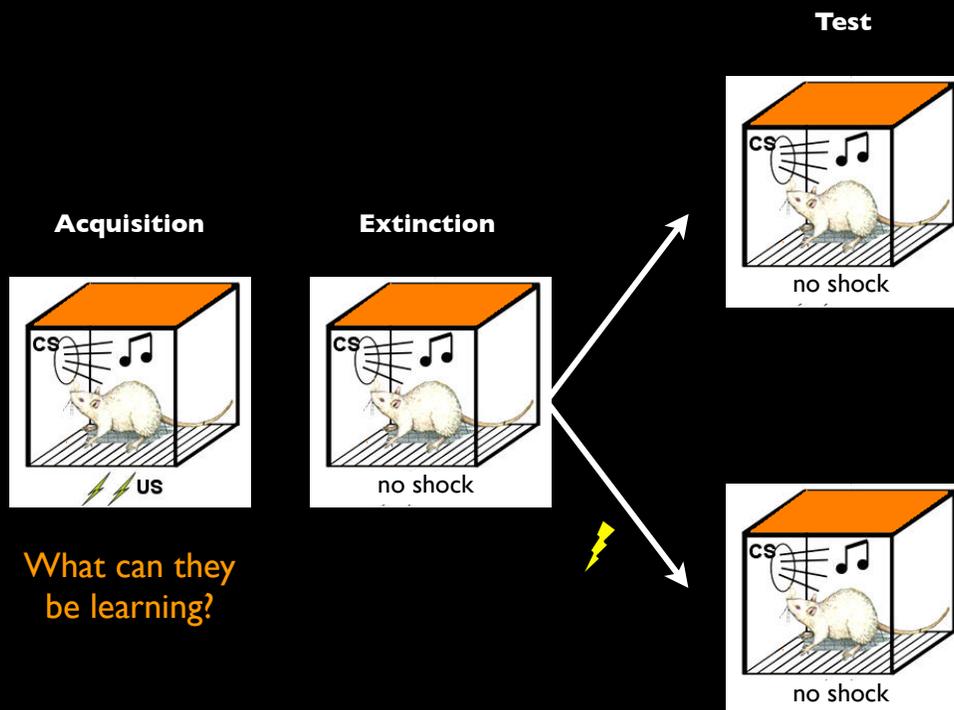


# What are animals *really* learning? The case of extinction



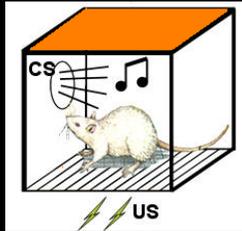
PSY/NEU338: Animal learning and decision making:  
Psychological, computational and neural perspectives

## Case in point: Reinstatement



# Extinction ≠ Unlearning

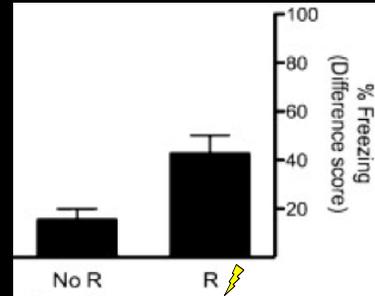
## Acquisition



## Extinction



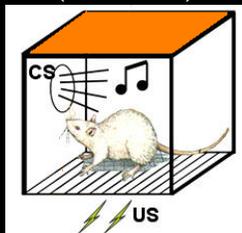
## Test



Storsve, McNally & Richardson, 2012

# Extinction ≠ Unlearning

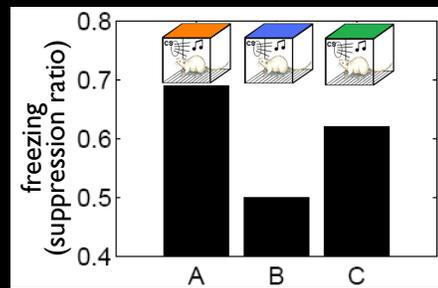
## Acquisition (Context A)



## Extinction (Context B)

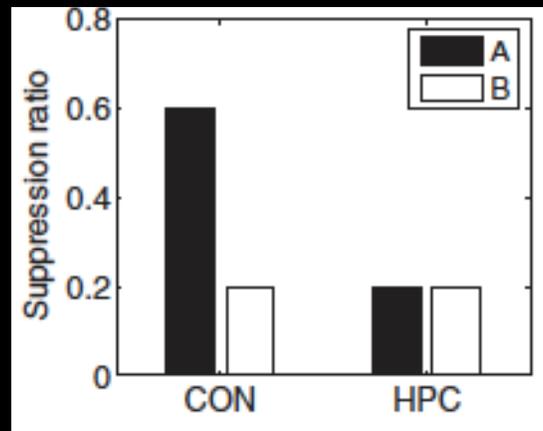


## Test (renewal)



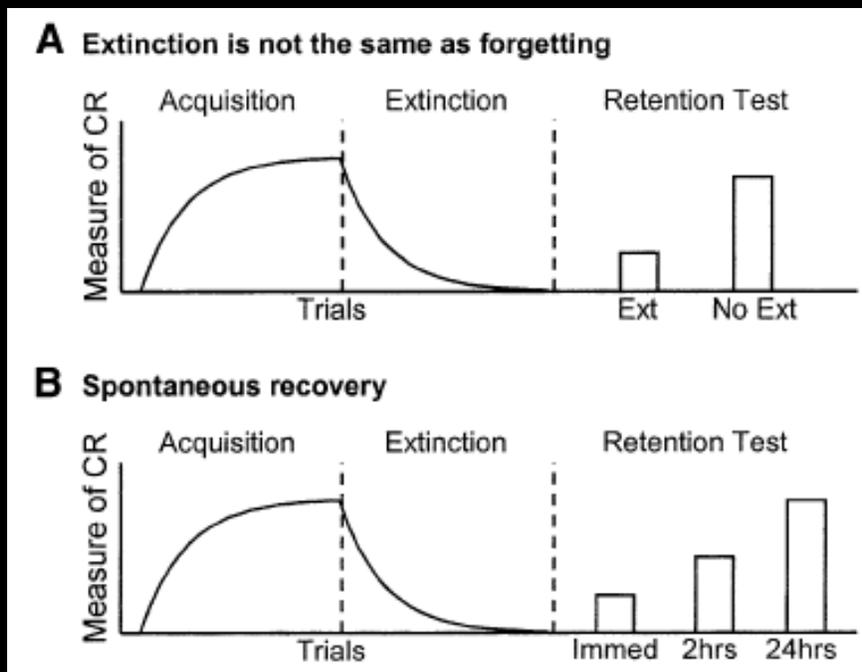
Bouton & Bolles 1979

And... this depends on integrity of hippocampus

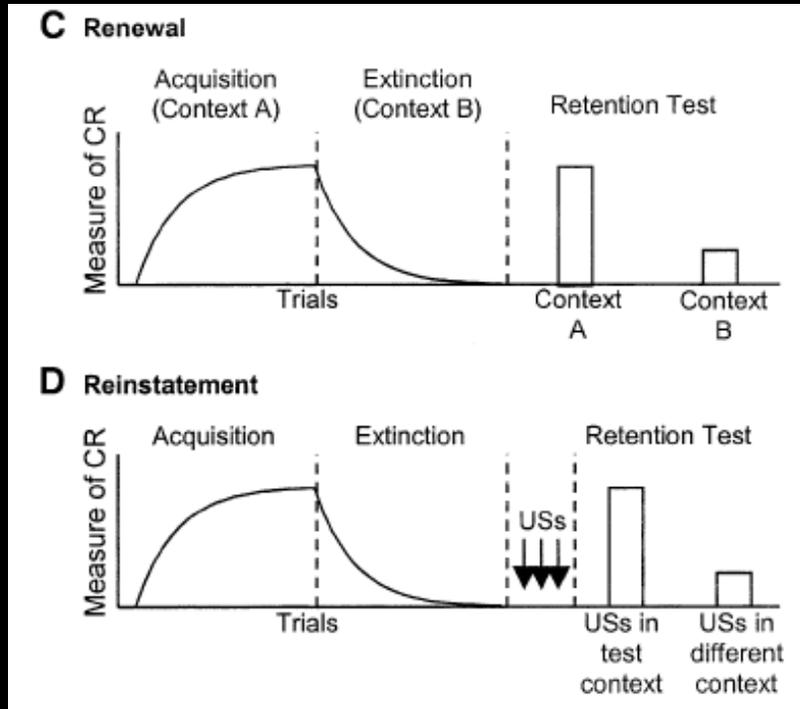


Ji & Maren 2005

Extinction does something, but not what we want it to do



## Extinction does something, but not what we want it to do



## Redish: Animals also learn the *states* of the task

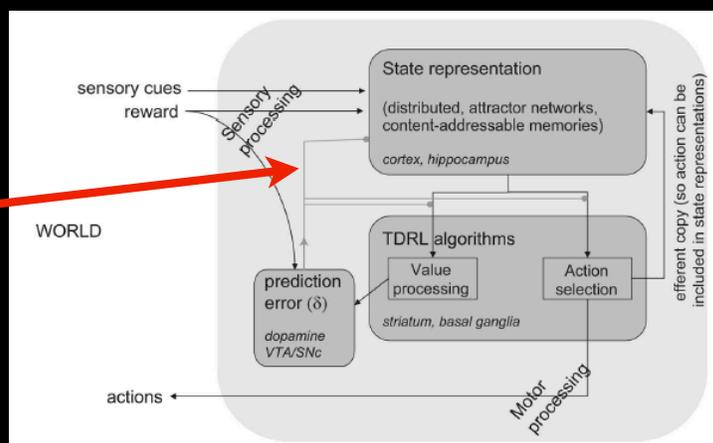
Psychological Review  
2007, Vol. 114, No. 3, 784–805

Copyright 2007 by the American Psychological Association  
0033-295X/07/\$12.00 DOI: 10.1037/0033-295X.114.3.784

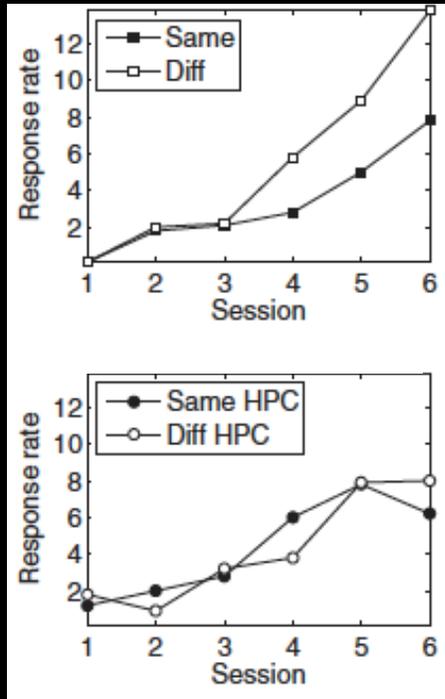
### Reconciling Reinforcement Learning Models With Behavioral Extinction and Renewal: Implications for Addiction, Relapse, and Problem Gambling

A. David Redish, Steve Jensen, Adam Johnson, and Zeb Kurth-Nelson  
University of Minnesota

idea: persistently negative prediction errors (low reward rate) cause splitting of new state



## But: this does not explain similar phenomena in LI



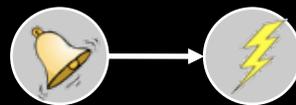
no LI if conditioning is in different context than preexposure

and this too depends on hippocampus... What is the hippocampus doing in these tasks?

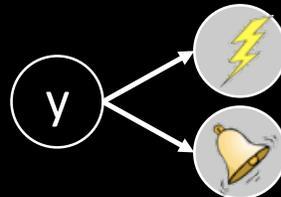
Honey & Good 1993

## going one step further: learning causal structure

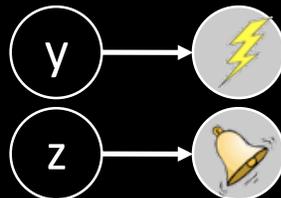
structure I:  
tone causes shock



structure II:  
latent variable (y)  
causes tone and shock



structure III:  
tone and shock caused  
by independent latent  
variables (y,z)



Sam Gershman

## Bayesian inference with an infinite capacity prior

Gershman, Blei & Niv 2010

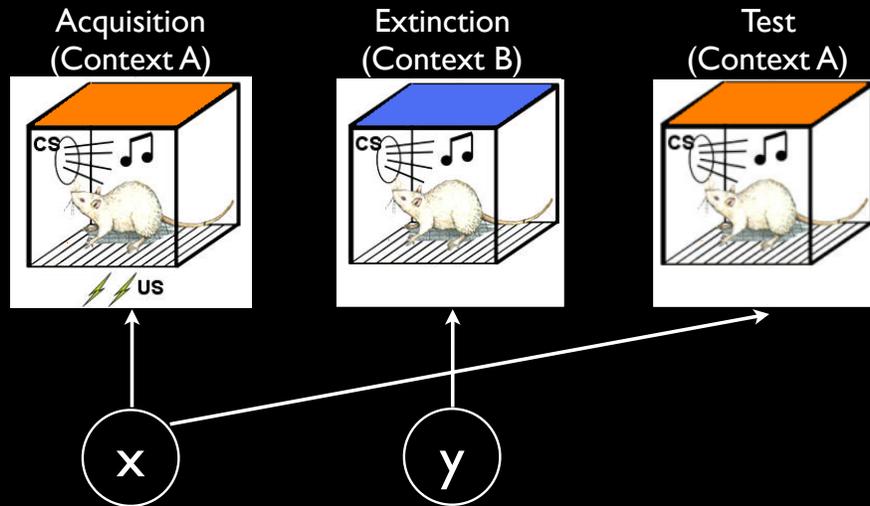
Hypothesis: Animals assume a *generative model* that is flexible enough to capture the complex structure of the environment, but constrained enough to allow learning

1. Each trial is caused by a **single** latent cause
2. Each latent cause tends to produce **similar** trials (ie, has a characteristic probability of “emitting” each of the stimuli)
3. All else equal, a (recently) **prolific** latent cause (ie, has caused many trials) is more likely to cause another trial
4. The number of possible latent causes is **unbounded**. That is, there is some (small) probability that the current trial is generated by a completely new latent cause

## Chinese Restaurant Prior (Infinite capacity mixture model)

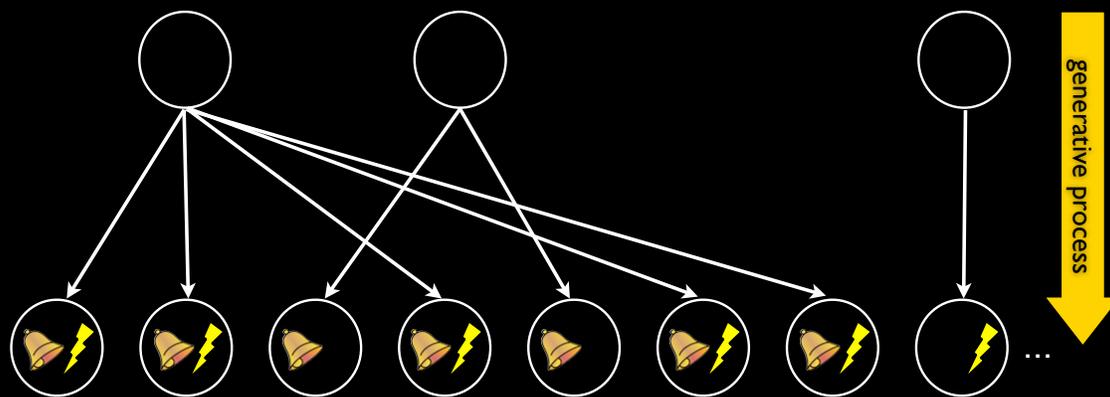


## A latent cause theory

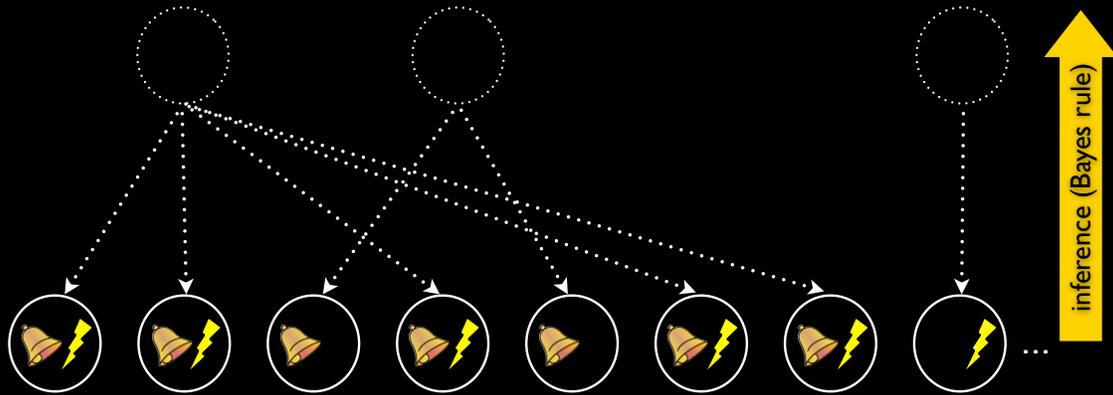


1. latent causes have characteristic emission probabilities
2. similarity between trials allows inference about the relevant latent cause

## Inference: "inverting" a generative model



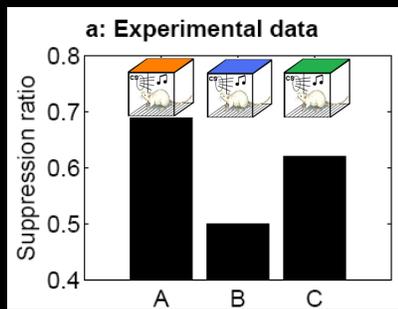
## Inference: "inverting" a generative model



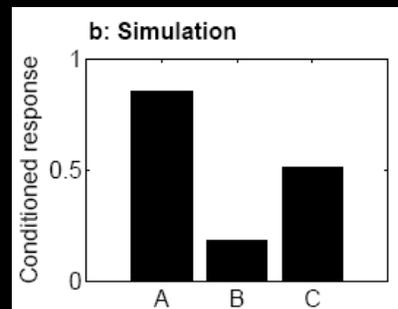
$$p(\text{cause}|\text{data}) \propto p(\text{data}|\text{cause})p(\text{cause})$$

## Model explains renewal of fear

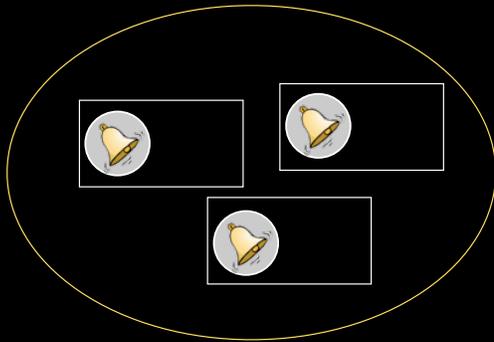
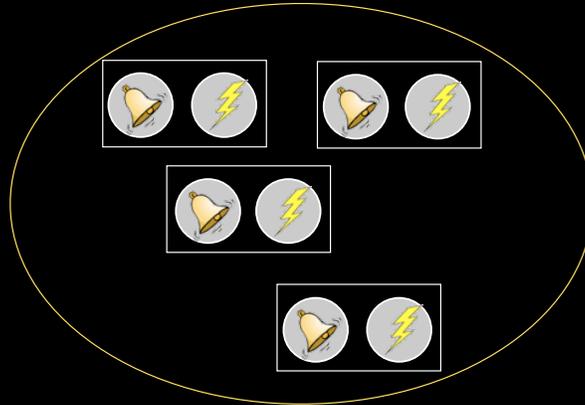
Gershman, Blei & Niv 2010



Bouton & Bolles 1979



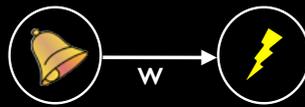
## Conditioning as clustering



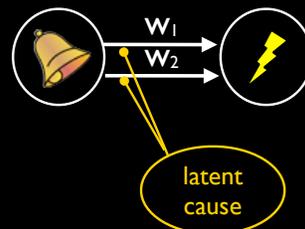
Within each cluster: "learning as usual"  
(Rescorla-Wagner, RL etc.)

## Equivalent to multiple associations

reinforcement learning  
(RW/TD) model

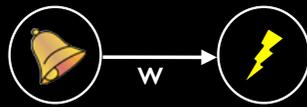


latent-cause modulated RL  
model

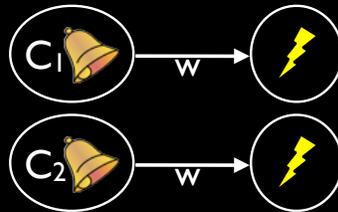


## Equivalent to “compound cues”

reinforcement learning  
(RW/TD) model

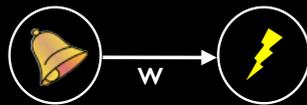


latent-cause modulated RL  
model

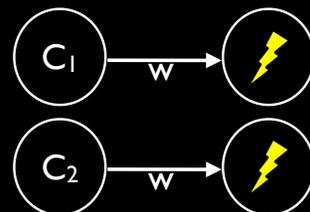


## Latent causes as states

reinforcement learning  
(RW/TD) model



latent-cause modulated RL  
model



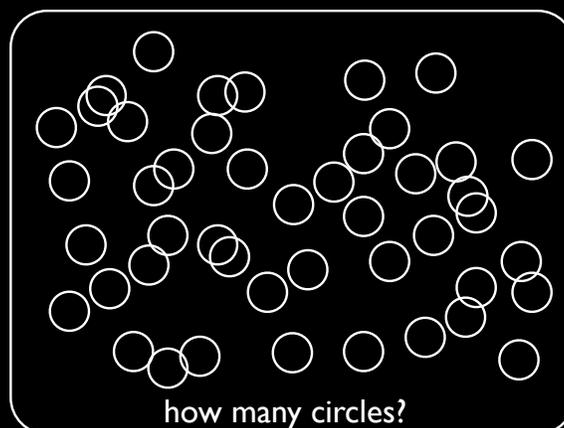


## Testing the model I : "Circles Task"

Gershman & Niv 2013

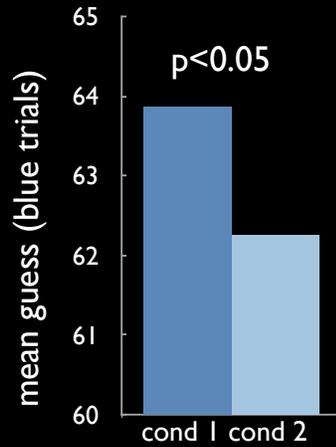
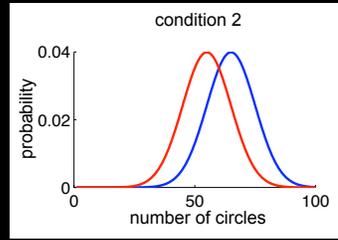
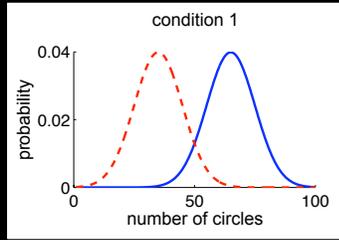
similarity is crucial for clustering observations

inference about latent causes determines "internal state"

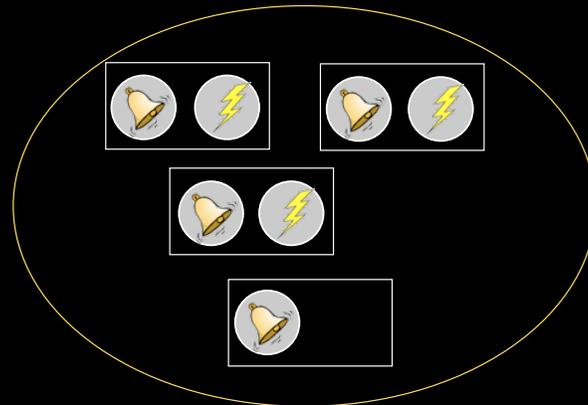


# Testing the model I : "Circles Task"

Gershman & Niv 2013

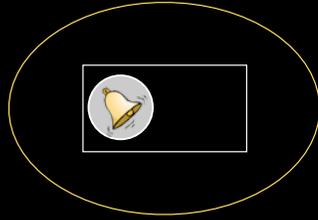
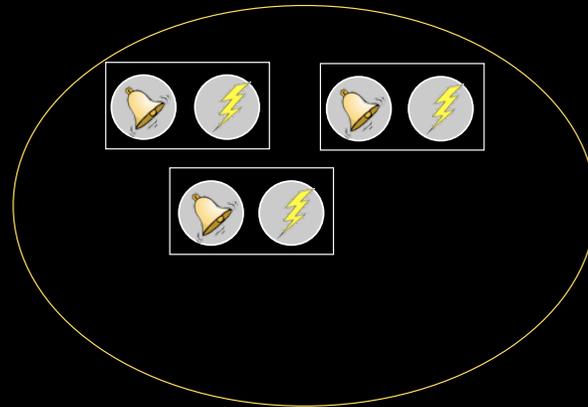


# A "battle" between learning and memory



*associative learning* (modify existing cluster)

## A "battle" between learning and memory



*structural learning*  
(create new state)

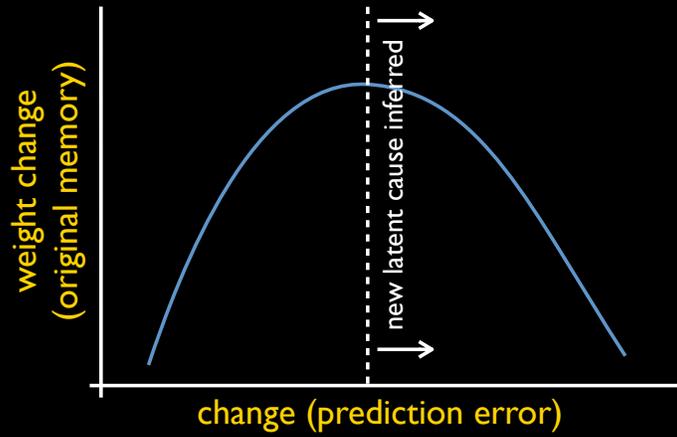
## Testing the model II: how to erase a fear memory

hypothesis: prediction errors (dissimilar data) lead to new states



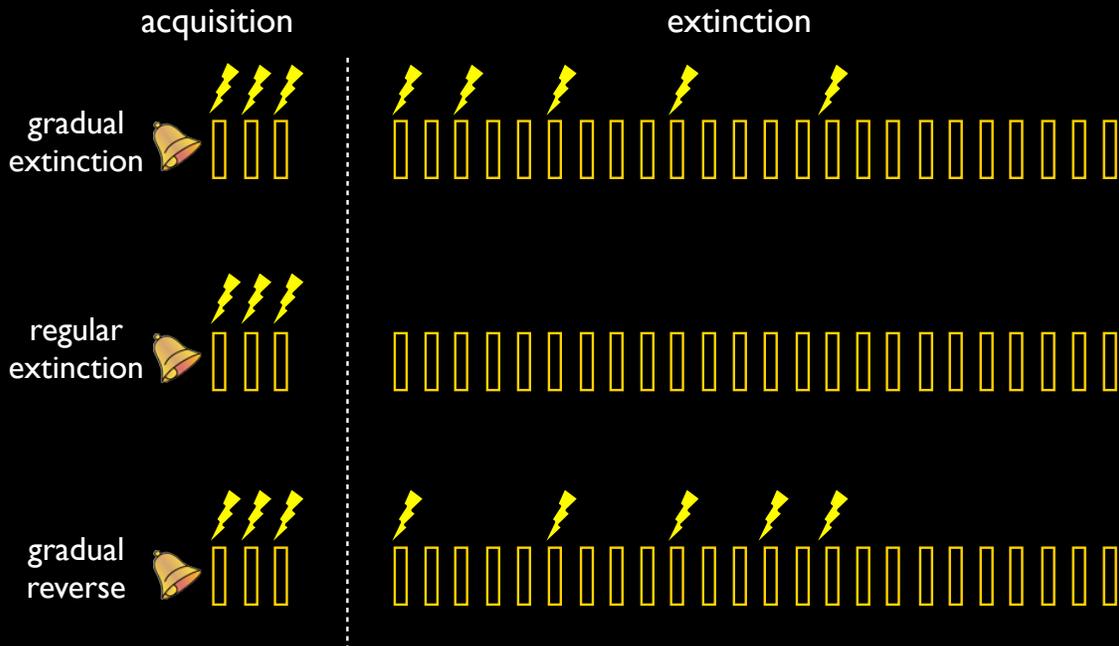
what if we make extinction a bit more similar to acquisition?

# Testing the model II: how to erase a fear memory



# Testing the model II: gradual extinction

Gershman, Jones, Norman, Monfils & Niv 2013

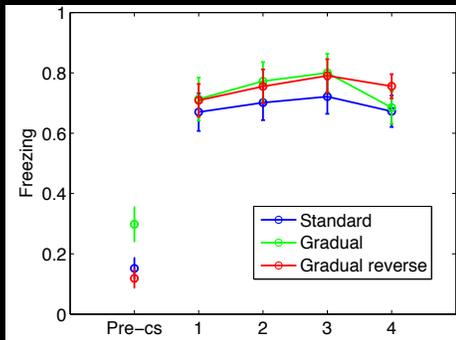


test one day (reinstatement) or 30 days later (spontaneous recovery)

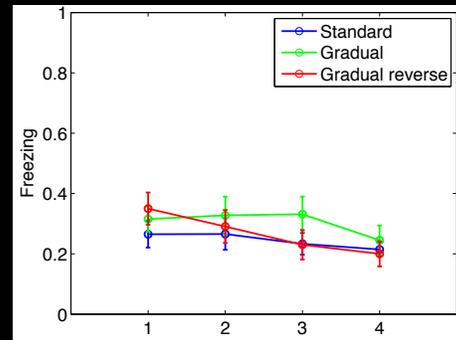
## Testing the model II: gradual extinction

Gershman, Jones, Norman, Monfils & Niv 2013

first trials of extinction

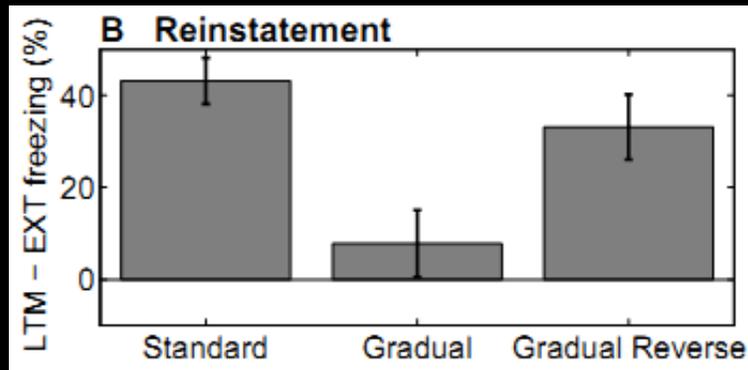


last trials of extinction



## Testing the model II: gradual extinction

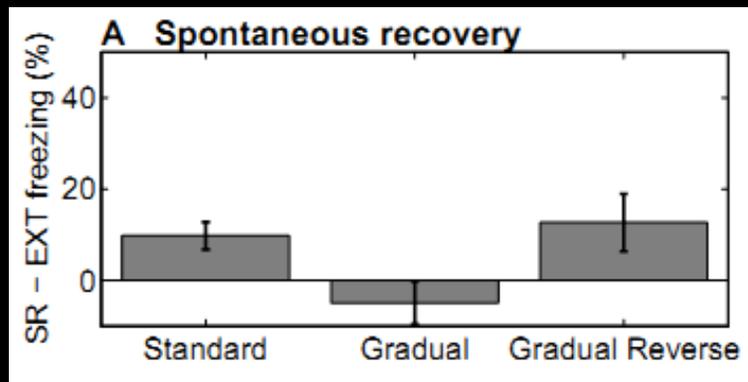
Gershman, Jones, Norman, Monfils & Niv 2013



only gradual extinction group shows no reinstatement

## Testing the model II: gradual extinction

Gershman, Jones, Norman, Monfils & Niv 2013

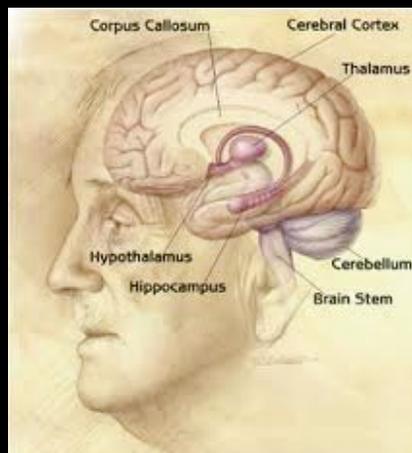


only gradual extinction group freeze LESS after 30 days than at the end of extinction (= no spontaneous recovery)

## Where does this “clustering” occur?

key decision: is current observation (trial) similar or different from previous observations?

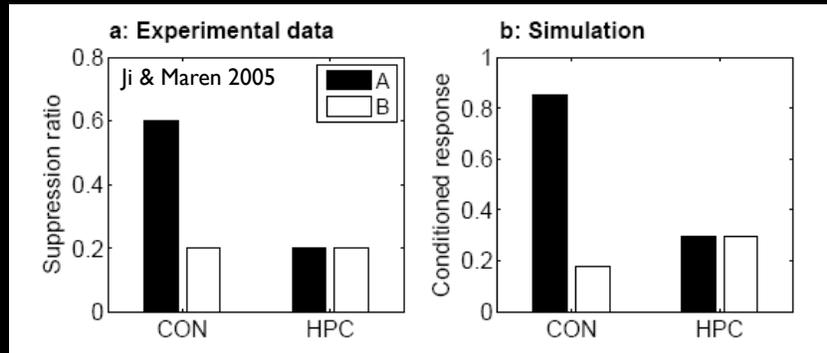
an expert in such decisions: HIPPOCAMPUS



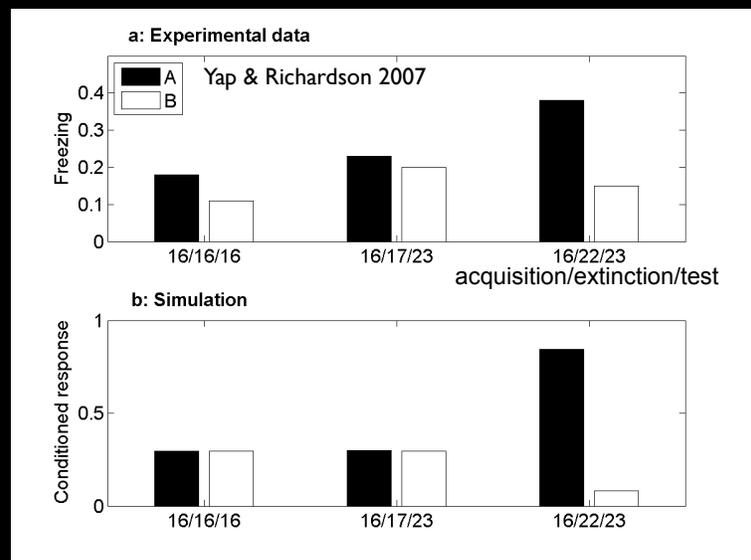
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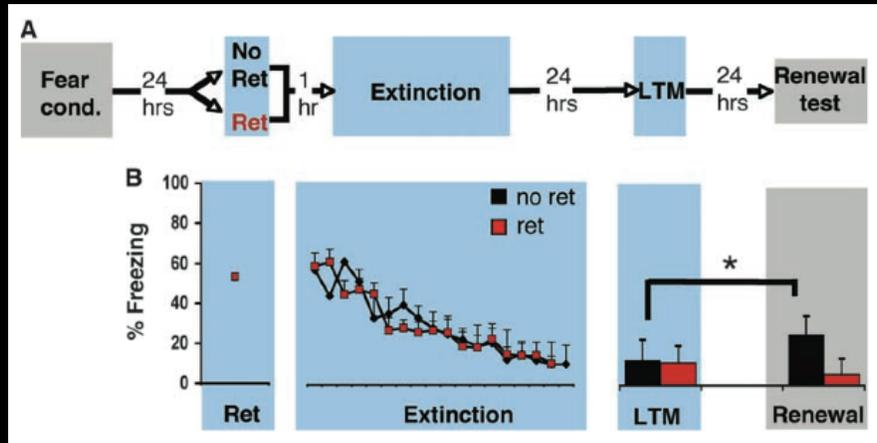
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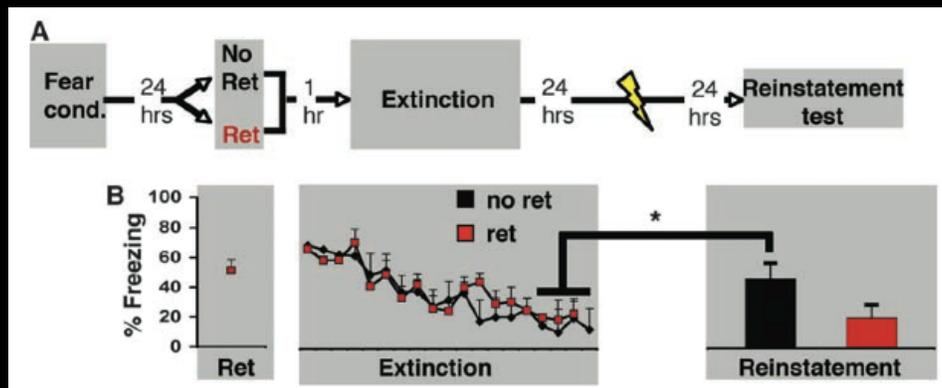
## Where does this “clustering” occur?



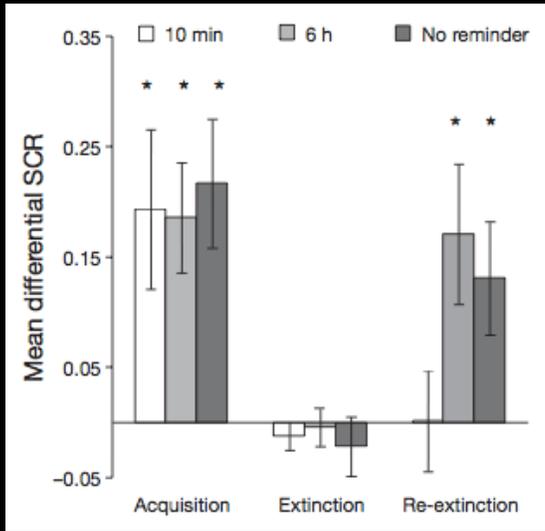
## But now the *really* crazy stuff: Monfils-Schiller paradigm



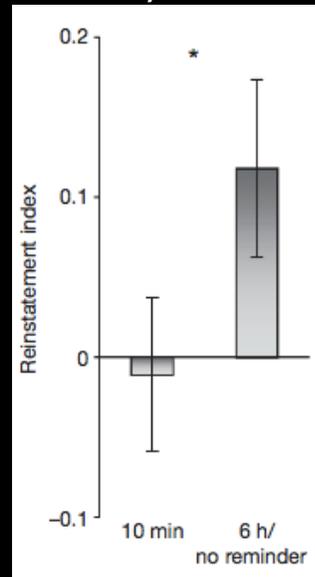
## But now the *really* crazy stuff: Monfils-Schiller paradigm



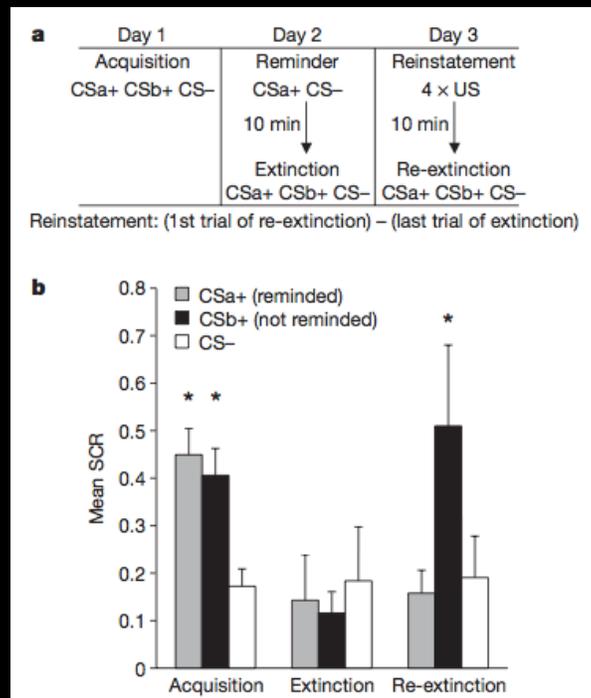
In case you are skeptic: this also works in humans...



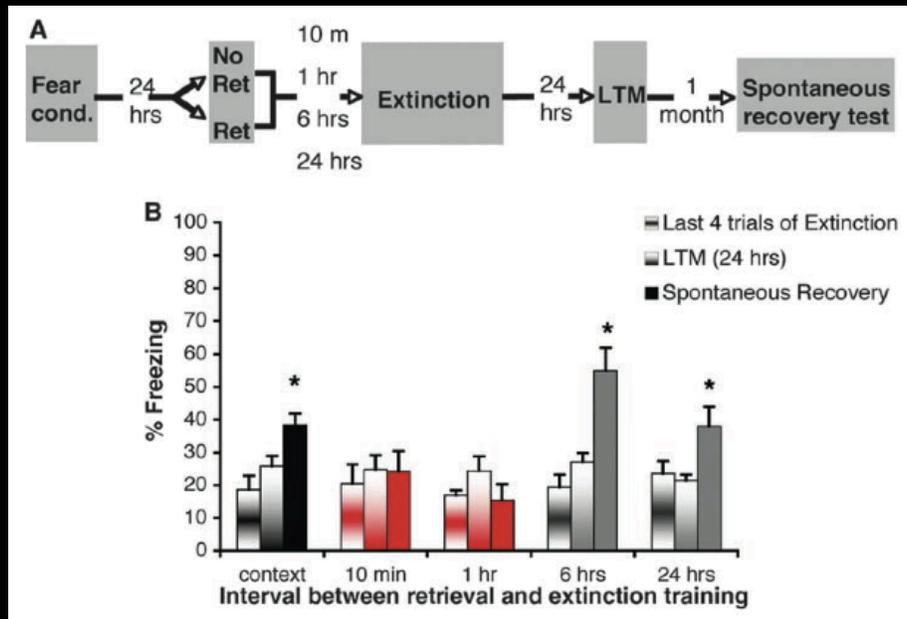
Even a year later!



In case you are skeptic: this also works in humans...

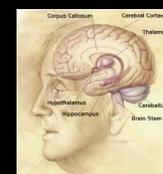
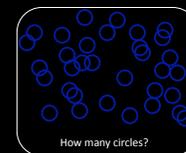
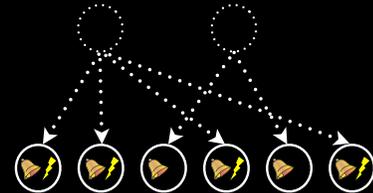


## An explanation: reconsolidation



## Summary

- Animals might be smarter than we think: make inferences about the **latent causes** of observations as part of prediction learning
- **similarity** determines when different observations will interfere with each other: **create a new memory or alter an old one?** **Inferred structure** determines the “battle” between learning and memory in the brain
- we can **control** memory modification by titrating **prediction errors**
- **memory is not just a passive record:** depends on the animal’s **beliefs** about the underlying causal structure (subjective!)
- potential interaction between **dopamine** and **hippocampus** in reinforcement learning



## Bayesian inference: what is all the hype about?

- random variables (discrete, continuous)
- probability distribution
- probability distributions as beliefs
- Bayes rule

## Bayesian inference: intuition

$$P(A|B) = P(B|A)P(A)/P(B)$$

$$P(\text{model}|\text{data}) = P(\text{data}|\text{model})p(\text{model})/p(\text{data})$$

- sometimes  $P(A|B)$  is really hard but  $P(B|A)$  is easy  
→ this is why inversion using Bayes rule helps
- eg. you saw 3 heads and 7 tails, what is the probability that the coin is fair?
- If the coin is fair, what is the probability of seeing 3 heads and 7 tails?
- eg. Brian says: "I'll pass" - what is Brian talking about?
- If Brian is talking about an exam, how probable is this sentence?

## The importance of priors in Bayesian inference

- interpretation of Bayes rule: we care about both prior and likelihood in inference
- eg. test for disease came out positive  
accuracy of test is 99%  
disease a-priori in 1/10000 people  
what are the odds that the patient has the disease?