

# Generalization and Discrimination: the “Grand Challenge” class



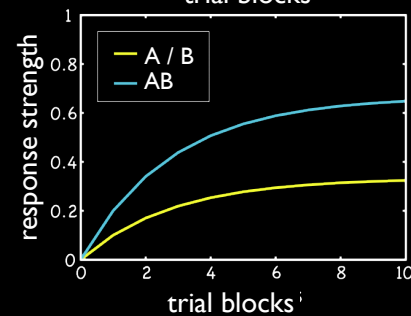
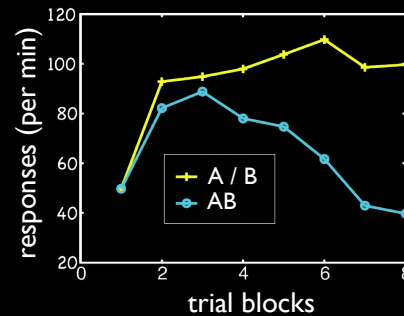
**PSY/NEU338: Animal learning and decision making:  
Psychological, computational and neural perspectives**

## Outline

- Today: Generalization, Discrimination
- Thursday: Elemental & Configural theories
- Latent cause models of generalization and discrimination, Bayesian model comparison

# Challenge 1: Negative Patterning (aka: the XOR problem)

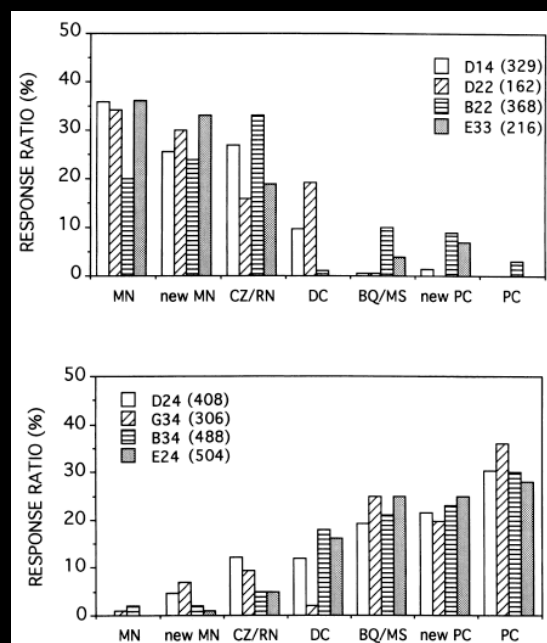
- animals can learn **nonlinear** problems such as negative patterning (XOR):
  - A+
  - B+
  - AB-
- this is problematic for R-W
  - why?
  - solution?
  - how would it work (what do you predict at end of training)?



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# Challenge 2: Generalization

- Basic phenomenon: after training with stimulus A, a stimulus A' that is similar to A will generate a CR as well
- But: smaller response (generalization decrement)
- less responding the more A' is different from A



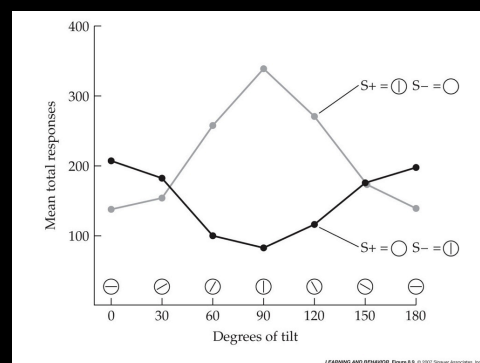
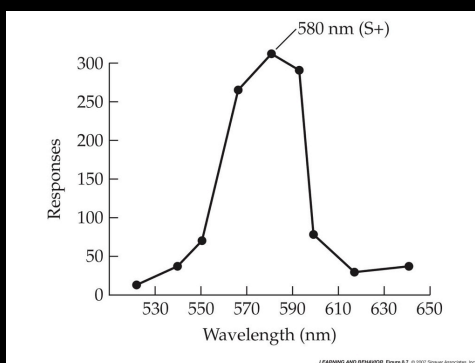
## Challenge 2: Generalization

- challenge: provide a theoretical explanation/ model
- hint: parsimony; use machinery you have already postulated

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## Challenge 2: Generalization

some problems?



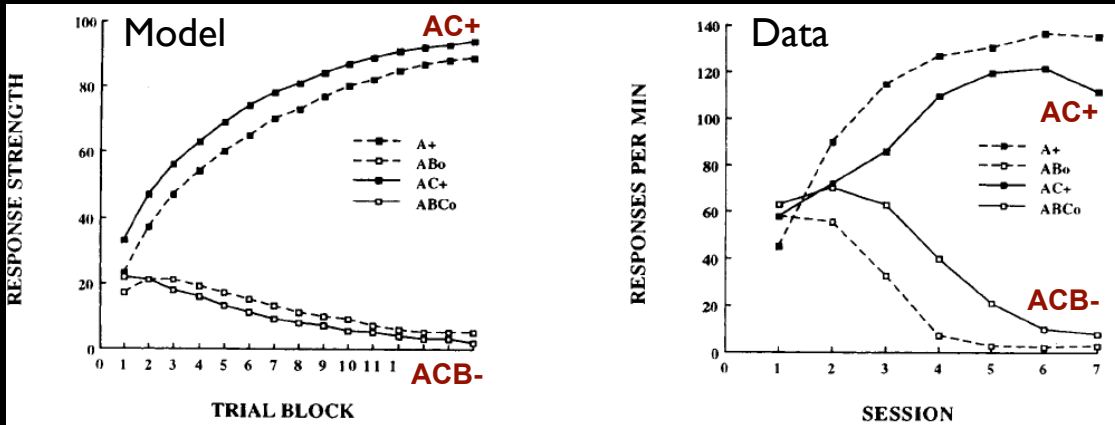
A+ and then presentation of AB: also see generalization decrement...

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# Challenge 3: Discrimination

(aka: more problems for elemental theory)

compare training of A+, AB- to AC+, ACB-  
 in which case would you expect better discrimination?

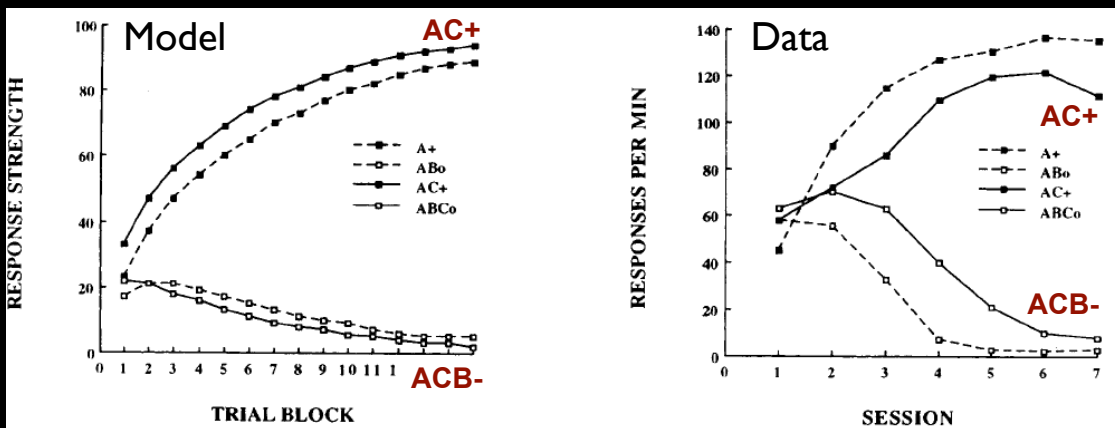


# Challenge 4: Discrimination

(aka: where there's a will, there's a way)

can you think of a solution? (hint: learning rates)

$$\Delta V_A = \frac{\alpha_A}{\alpha_T} (R - V_T)$$

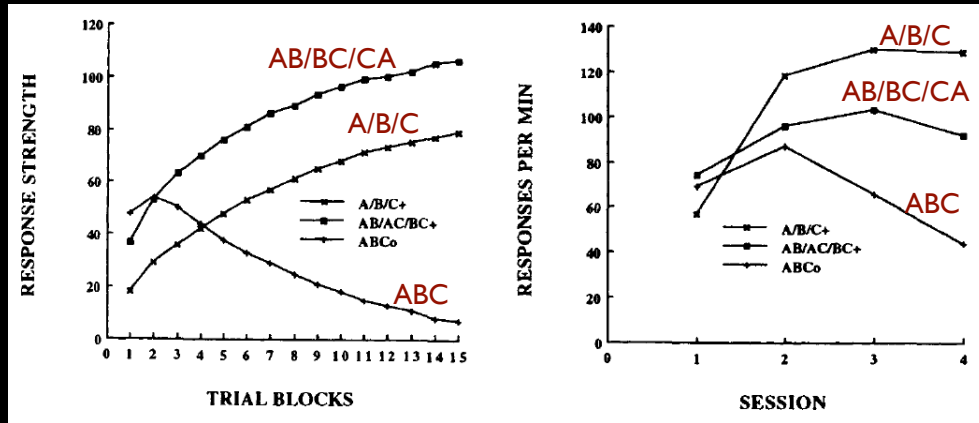


# Challenge 5: Generalization

(aka: but you never win)

but: train A+, B+, C+, AB+, BC+, CA+, ABC-

would animals *respond* more to A/B/C or to AB/BC/CA?  
what does the theory predict?



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## Pearce: Configural Theory

- presentation of a stimulus  $x$  activates several units  $j$
- prediction ( $V_{total}$ ) determined by all units weighted by similarity  $s(x,j)$

$$V_{total} = \sum_j s(x, j) V_j$$

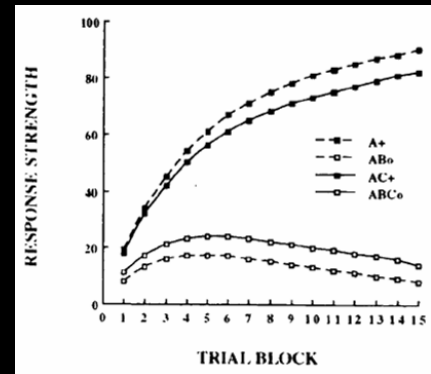
- learning occurs only for configural unit  $x$  that represents the current stimulus as a whole

$$V_x^{new} = V_x^{old} + \alpha_x (R - V_{total})$$

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# Configural Theory: Results

- explains: blocking, overshadowing, negative patterning, etc. (how?)
- predicts symmetric generalization from AB to A as from A to AB
- makes quantitative predictions:  $A+, AB- \Rightarrow B$  is inhibitory (why?)
- explains the results that elemental theories had problems with



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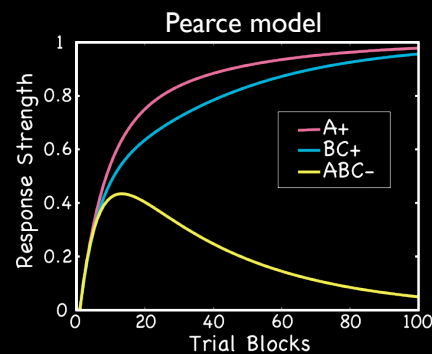
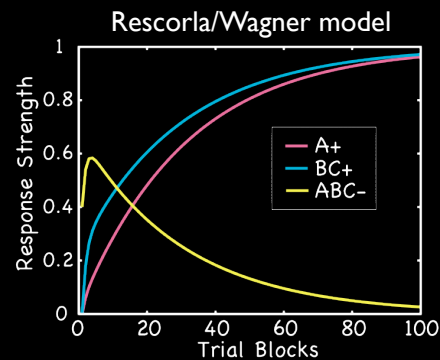
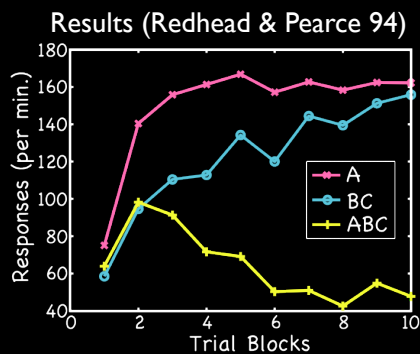
# Configural Theory: explains generalization

Training:

A+

BC+

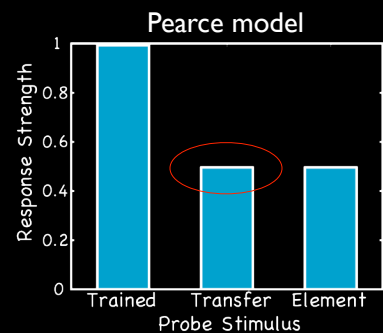
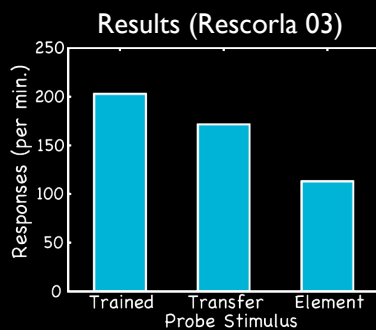
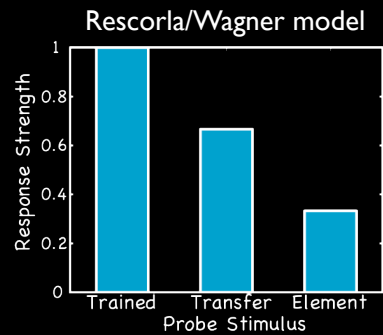
ABC-



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# but: doesn't show summation

- Training: AB+, CD+
- Test:
  - AB, CD (trained)
  - AC, BD (transfer)
  - A, B, C, D (elements)



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## Summary so far: elemental versus configural theories

- Elemental:
  - all active elements form an association with the US
  - emphasis on cases in which there is summation of the effects of different stimuli
- Configural:
  - in each trial only one association is created/updated
  - emphasis on similarity between stimuli: determines difficulty of discriminating between them
- In some sense, the question is really: are these predictors predicting different rewards (then I should sum them) or the same reward (then I should not; maybe update my confidence)

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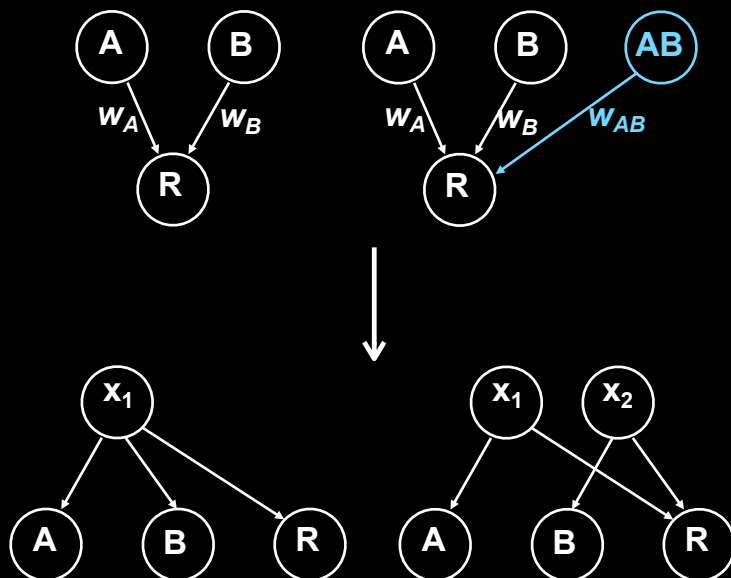
## an alternative view: both are right, but...

### 3 important questions

- under what conditions should we create a new configural unit and when should we just sum up the component elements?
- when a stimulus is presented, how do we generalize from it to other known stimuli?
- how should learning be distributed between the different units of representation?
- remind you of something?

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## learning as inference



- rather than posit causal relationships between observed events only....
- latent cause models, Bayes' rule to infer latent causes
- use observed data to infer the model most likely to generate the data



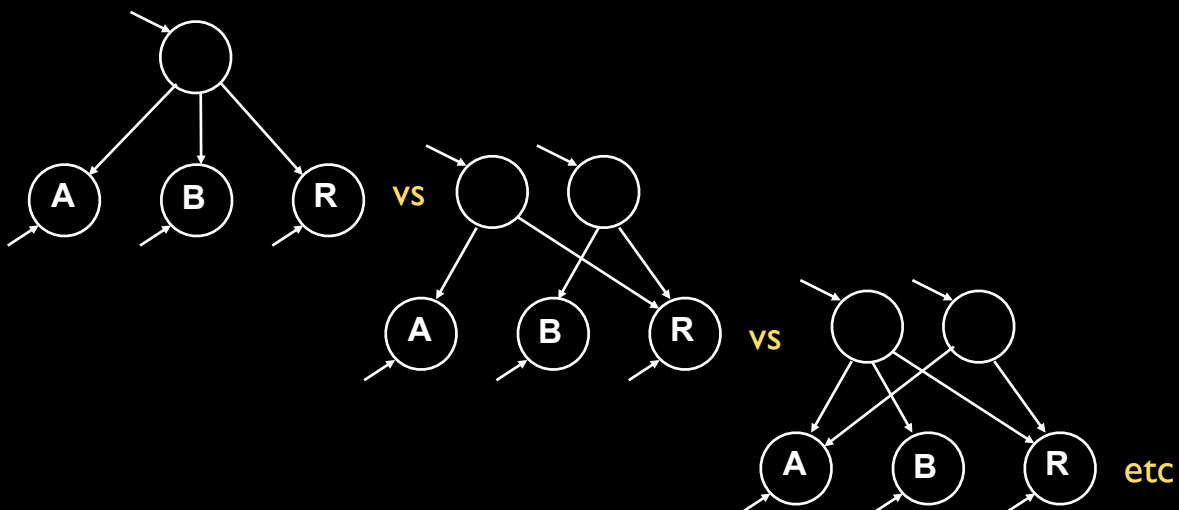
# Should I create another latent cause? What will be our guiding principle? (aka: where do we go from here?)

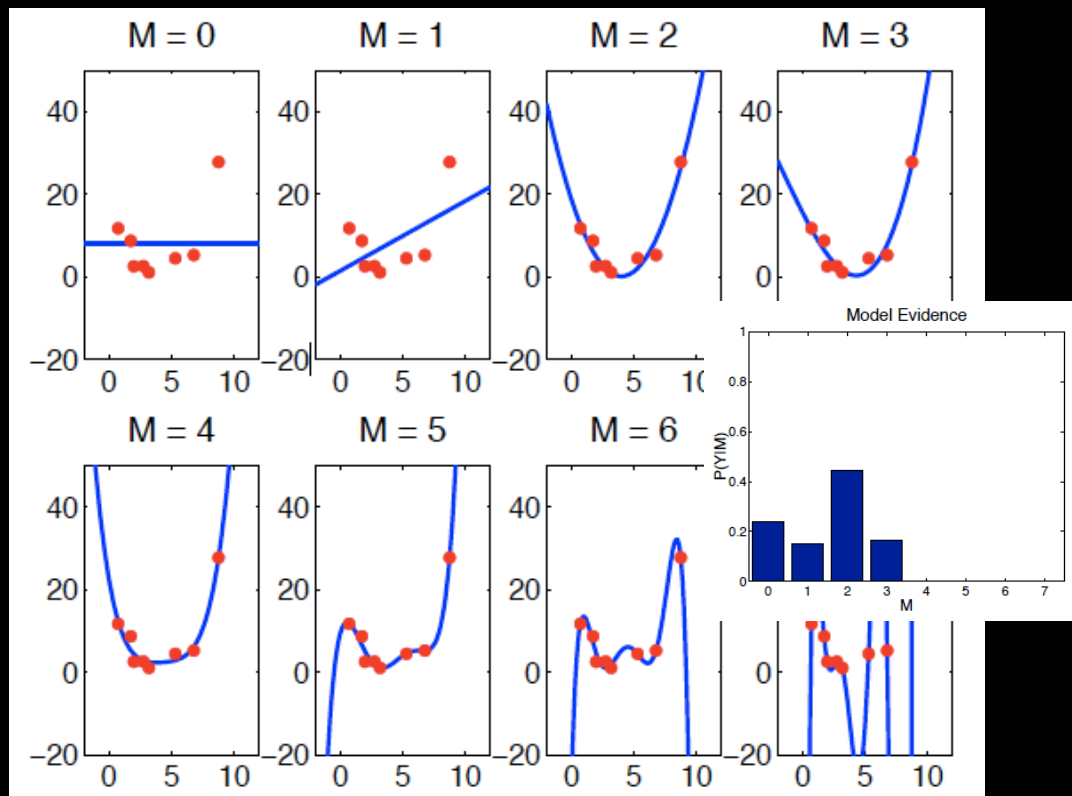
- "Pluralitas non est ponenda sine necessitate" Plurality should not be posited without necessity – William of Ockham (1349)
- we (the animal, the learner) should go for the **simplest** model of the environment that explains the data

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## inferring structure of a causal model

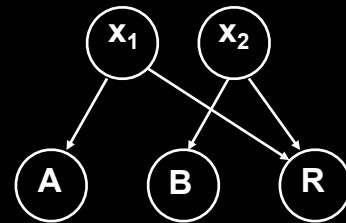
which 'configural units' are indicated by the data?





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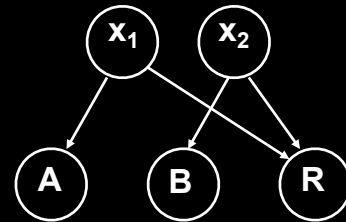
## back to Courville's model: making predictions



- goal:  $P(R|\text{stimuli}, \text{data}) = ?$
- data = all trials so far; stimuli = in this trial
- averaging (marginalization) over *all possible models*, weighted by their likelihood  

$$P(R|S, \text{data}) = \sum_M \int dw P(R|S, M, w) P(w|M, \text{data}) P(M|\text{data})$$
- somewhat similar to Pearce: a cause is likely to be 'on' if it causes observations that are similar to the current configuration of stimuli

# simplicity vs. accuracy

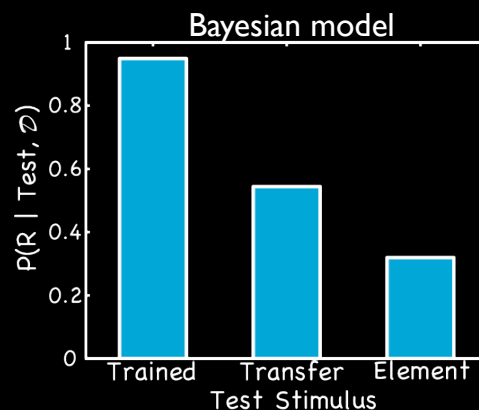
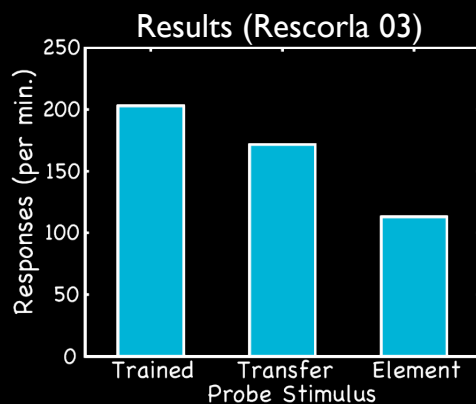
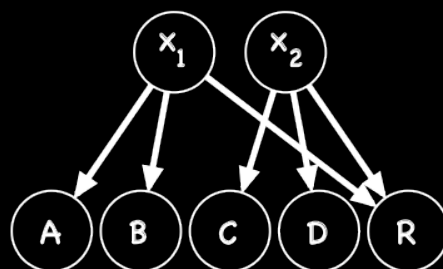


- start with prior that prefers smaller and simpler models: fewer units and connections, small weights
- as more data are observed, the prior **loses its influence** and the data 'take over'
- (coin toss example)
- this is the trademark of Bayesian inference: tradeoff between **simplicity** to **fidelity to data**
- (note: in Bayesian inference the posterior on one trial is the prior on the next trial)

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# results I: summation

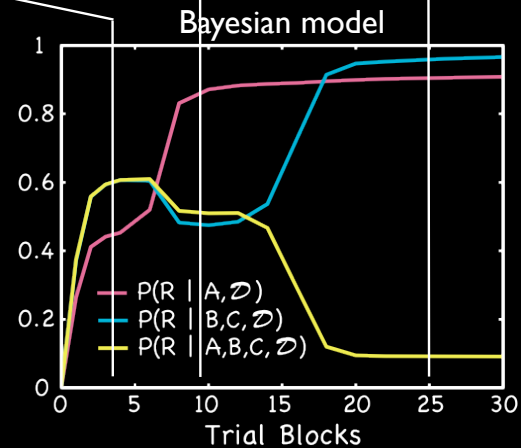
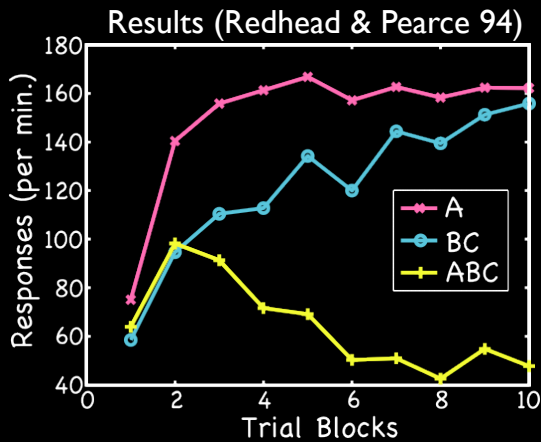
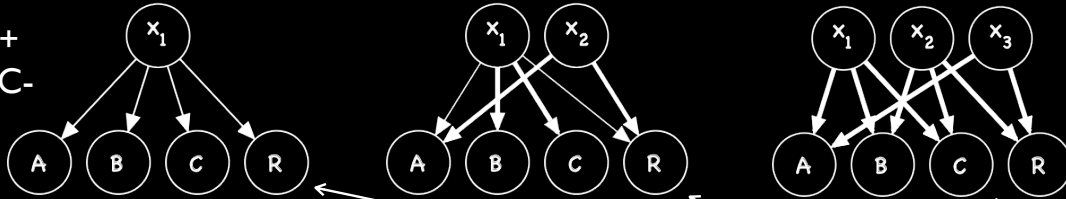
- training: AB+, CD+
- test: AB, CD (trained)  
AC, BD (generalization)  
A,B,C,D (elements)



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## results II: generalization & discrimination

A+  
BC+  
ABC-



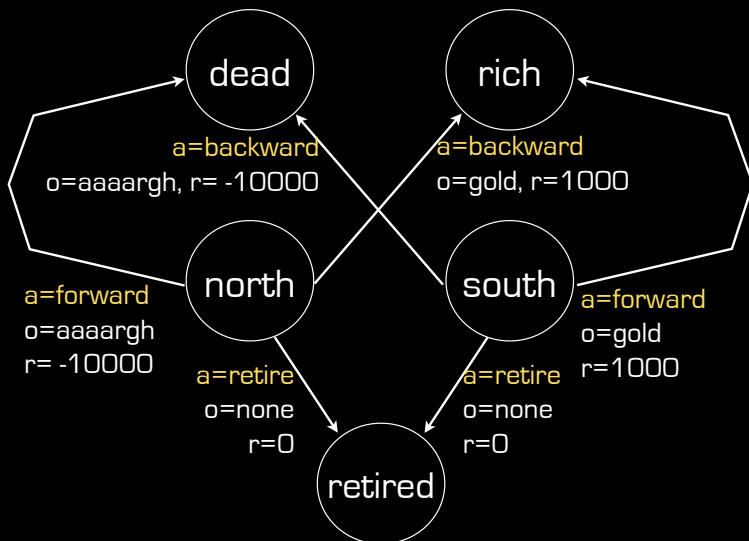
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## Summary so far: generative models and inference

- idea: our brain tries to infer a **causal model** of the world, given the **observations** we make
- strong assumption: causality, things are not random
- much evidence for **Bayesian inference** in the brain: we take into account priors and likelihood to make sense of the world
- how are these **computations** realized **algorithmically** and **neurally**?

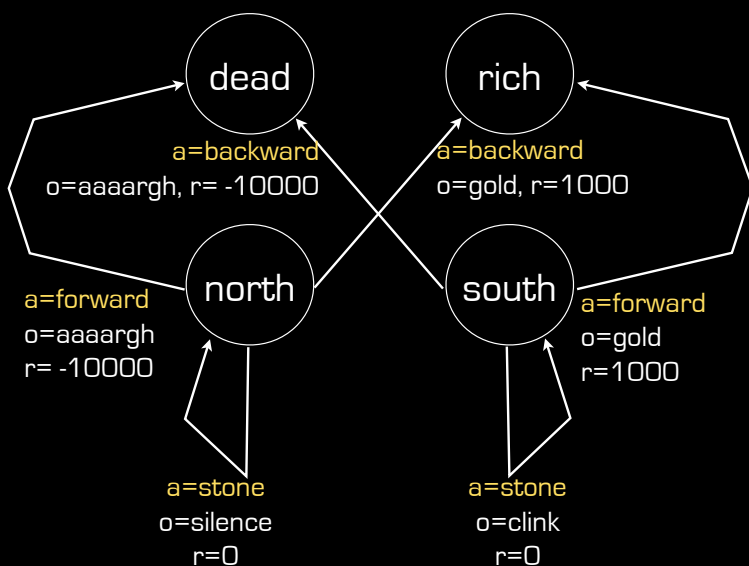
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## Problem: Between a cliff and a pot of gold [in the dark]



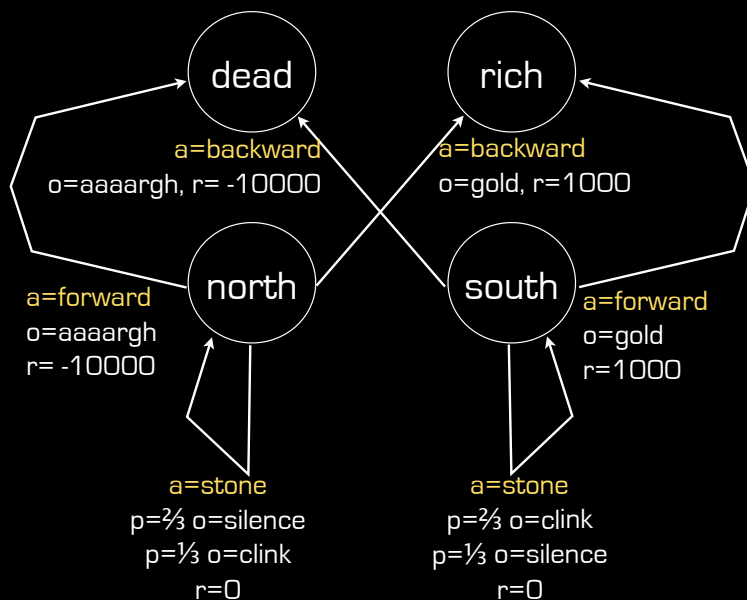
- what is the optimal policy?

## Example: Between a cliff and a pot of gold [in the dark]



- information gathering action

## Example: Between a cliff and a pot of gold [in the dark]



- what to do in this case?
- integrate multiple observations across time

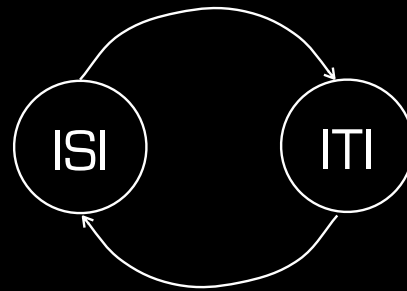
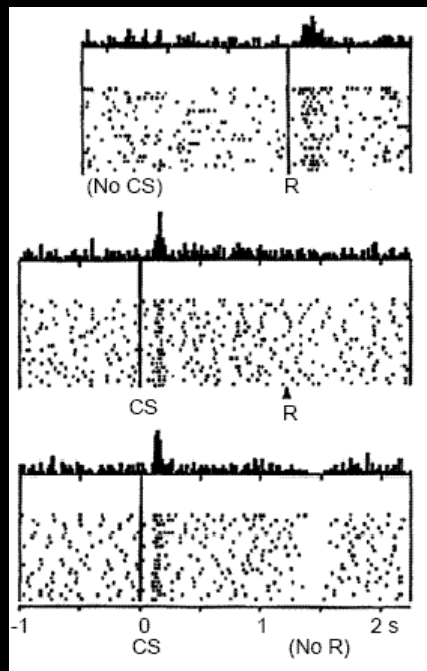
## Solving POMDPs: belief states



given a model of the environment (transition & observation functions)

- infer hidden state using observations, model and Bayes rule
- produces **distribution** over hidden states  
 $p(\text{north} \mid \text{clink}) \propto p(\text{clink} \mid \text{north}) p(\text{north})$
- distribution is called “**belief state**”
- **belief states themselves form an MDP!** (Kaelbling et al 1995)

## Belief states in the brain?



## Belief states in the brain?

Vol 447|28 June 2007|doi:10.1038/nature05852 nature

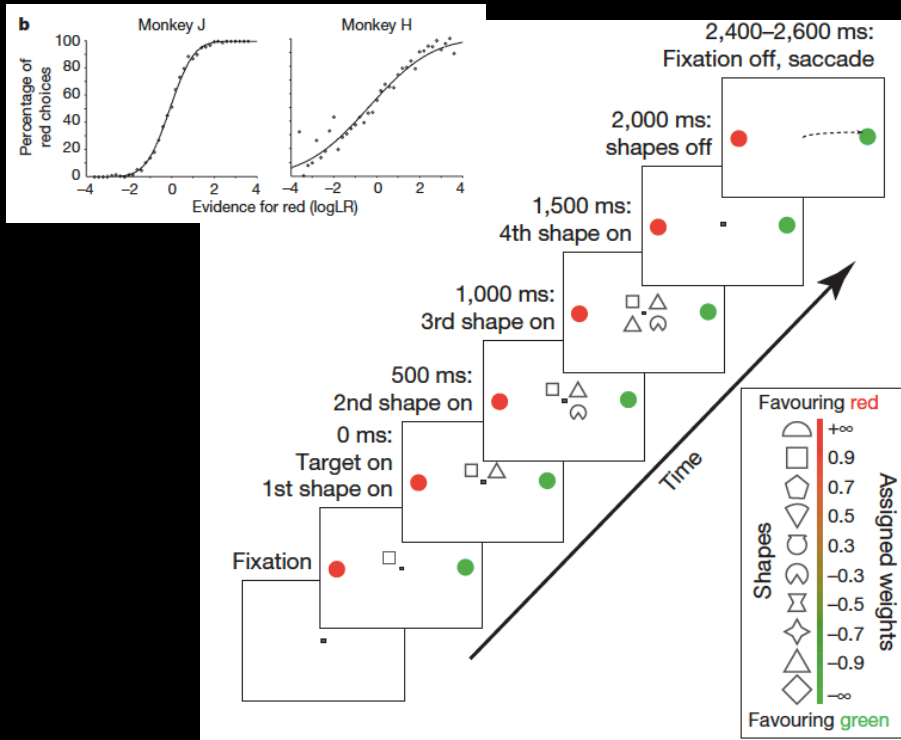
ARTICLES

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# Probabilistic reasoning by neurons

Tianming Yang<sup>1</sup> & Michael N. Shadlen<sup>1</sup>

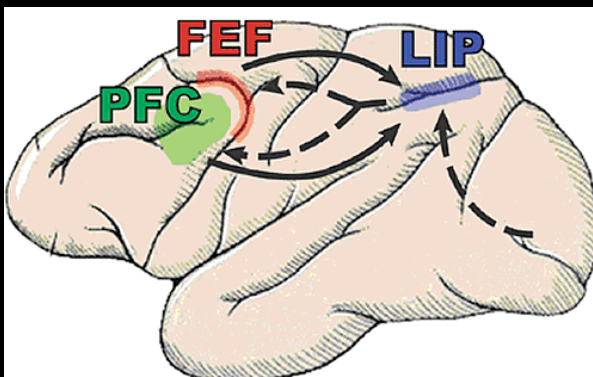
## Belief states in the brain?



## What are these neurons doing?

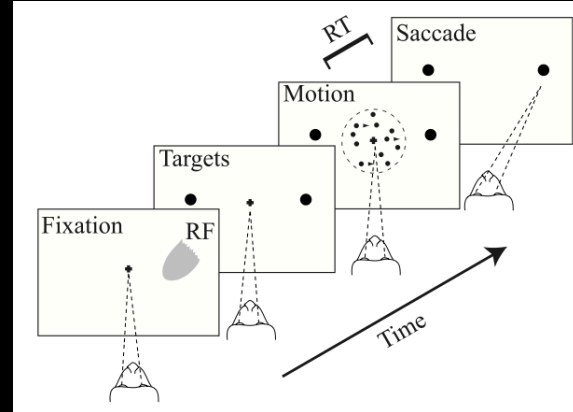
Accumulation of information from visual cortex  
 calculate belief state as the (log) ratio of likelihoods:

$$\frac{p(\text{gold} | \text{observations})}{p(\text{cliff} | \text{observations})} = \frac{p(\text{observations} | \text{gold}) p(\text{gold})}{p(\text{observations} | \text{cliff}) p(\text{cliff})}$$



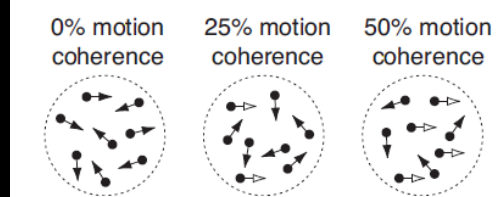


## Another example: random dot motion



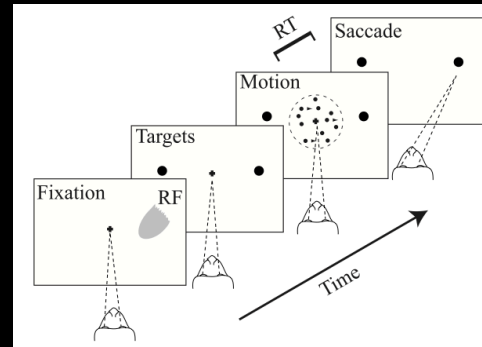
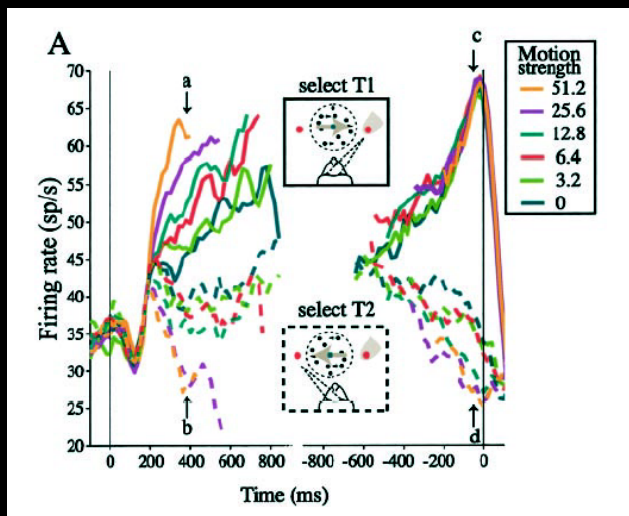
you don't know if dots are moving right or left...

...at each point respond "right" or "left" or gather another burst of (noisy) information



Shadlen et al. (after Newsome, Movshon)

## Integration to a bound



Roitman & Shadlen 2002

## Summary so far...

- POMDPs as framework for thinking about real world learning tasks: incorporating **sensory uncertainty** into RL
- separates model-based inference of state (in perceptual areas) from learning in basal ganglia (dopamine etc.)
- MT→LIP→FEF: example for perception as accumulation of evidence for action
- [Note: both types of problems, perceptual judgements and instrumental conditioning, called “decision making” though they are very different]
- for more info: <http://www.youtube.com/watch?v=NEklxOwdxs>

## before you go: quick 1 minute paper

- participation/activities in class: love or hate?
- if you hate them: which type did you least hate?  
how could these be made nicer for you?
- if you like them: which type would you least miss?  
how can these engage more students?