

# Models of Conditioning

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# Conditioning

- Pavlovian (classical) conditioning
  - learning predictions of value
    - me: basic paradigms, simple Bayesian model
    - John: alternative 'locally Bayesian' framework
    - Nathaniel: statistical models of representation, competition and cooperation
    - Bernard: neural substrates for predictions
    - me: models of value
    - Nathaniel: fMRI of value
- Instrumental (operant) conditioning
  - learning actions (RL)
    - Bernard: different neural systems for action control
    - me: models of habitual control
    - Nathaniel: models of competition

# Pavlovian Conditioning

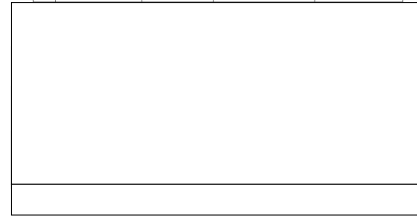
$$L \rightarrow r$$



- predictive relationship
- stimulus (L: light),
- biologically significant outcome (r: reward or punishment)
- present L; monitor behaviour
  - preparatory (approach, withdrawal)
  - consummatory (eating)
- evolutionary 'prior' – bias/variance

# Pavlovian Conditioning

|   | Name      | Set 1 | Set 2 | Test  |
|---|-----------|-------|-------|-------|
| 1 | Pavlovian |       | L → r | L → r |



- competing/cooperating predictors
  - competition for learning/prediction
- initial, and sometimes continual, uncertainty
- conditional vs joint distribution (Daw)

# Marrian Levels of Analysis

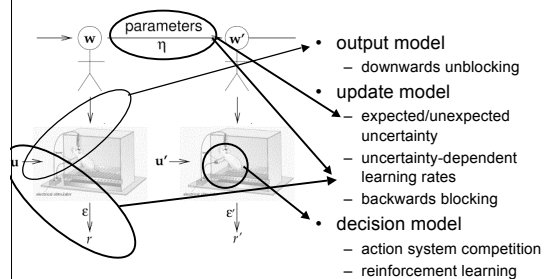
- computational
  - prior; likelihood; crank
- psychological
  - online learning rules



$$\Delta w_T = \phi_T(r - V)u_T$$

- neural
  - associabilities (amygdala); errors (VTA); representations (cortex)

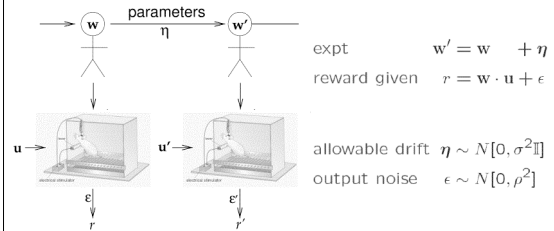
# Computational Conditioning



## Psychological Intuitions

- contiguity (causality)
  - fine for  $L \rightarrow r$
  - but blocking:  $L \rightarrow r$ ;  $L+T \rightarrow r$ ;  $T \rightarrow \cdot$
- error correction Rescorla-Wagner  $(r-V)u_T$ 
  - but  $\leftarrow$ -blocking:  $L+T \rightarrow r$ ;  $L \rightarrow r$ ;  $T \rightarrow \cdot$
- associability – learning competition
  - Mackintosh: GPGP
  - Pearce & Hall: AOAA
  - but  $L \rightarrow 2r$ ;  $L+T \rightarrow r$ ;  $T \rightarrow -r$
- competitive prediction
  - Kruschke; Long & Dayan; Daw

## Kalman Filter



- Markov random walk (or OU process)
- no punctate changes
- additive model of combination
- forward inference

## Kalman Posterior

The Kalman filter maintains uncertainty:

$$P(V) = \mathcal{N}[\hat{w} \cdot u, u \cdot \Sigma \cdot u]$$

where



## Assumed Density KF

Diagonal approx to  $\Sigma = \text{diag}(\sigma_i^2)$

If  $w \sim \mathcal{N}[\hat{w}, \text{diag}(\sigma_i^2)]$ , then

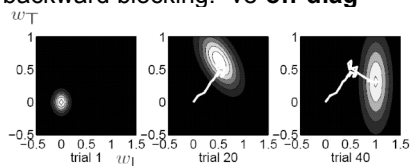
$$\Delta \hat{w}_i = \frac{\sigma_i^2}{\sum_j \sigma_j^2 + \rho^2} (r - u \cdot \hat{w}) u_i$$

- Rescorla-Wagner error correction
- competitive allocation of learning
  - P&H, M

## Blocking

|          |                     |                     |                       |
|----------|---------------------|---------------------|-----------------------|
| forward  | $L \rightarrow r$   | $L+T \rightarrow r$ | $T \rightarrow \cdot$ |
| backward | $L+T \rightarrow r$ | $L \rightarrow r$   | $T \rightarrow \cdot$ |

- forward blocking: error correction  $(r - u \cdot \hat{w})$
- backward blocking: -ve **off-diag**  $\Sigma_{LT} < 0$



## Mackintosh vs P&H

- under diagonal approximation:
 
$$E(r - u \cdot \hat{w})^2 = \rho^2 + \sum_j \sigma_j^2 u_i^2$$
- for slow learning,  $\sigma_j^2$  changes with correlation of  $(r - V)$  and  $u_i$ 
  - effect like Mackintosh

## Summary

- Kalman filter models many standard conditioning paradigms
- elements of RW, Mackintosh, P&H
- but:
  - downwards unblocking  
 $L \rightarrow r \Delta r \quad L+T \rightarrow r \quad T \uparrow \pm r$   
 predictor competition
  - negative patterning  $L \rightarrow r; T \rightarrow r; L+T \rightarrow \cdot$
- stimulus/correlation rerepresentation (Daw)
  - recency vs primacy (Kruschke)

## Uncertainty (Yu)

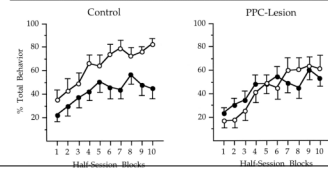
- expected uncertainty - ignorance  
 $w \sim \mathcal{N}[\hat{w}, \text{diag}(\sigma_i^2)]$ 
  - amygdala, cholinergic basal forebrain for conditioning
  - basal forebrain for top-down attentional allocation?
- unexpected uncertainty – ‘set’ change
  - noradrenergic locus coeruleus
- unexpected uncertainty – ‘state’ change
  - noradrenergic locus coeruleus
- part opponent; part synergistic interaction

## ACh in Conditioning

- Given **uncertainty**, ACh boosts learning to stimuli of uncertain consequences

Table 1. Outline of procedures for Experiment 1

| Treatment condition (groups) | Phase 1: consistent L-T relation | Phase 2: experimental change in L-T relation | Phase 3: test of conditioning to L |
|------------------------------|----------------------------------|--|------------------------------------|
| Consistent (CTL-C, PPC-C)    | L → T → food; L → T              | L → T → food; L → T                          | L → food                           |
| Shift (CTL-S, PPC-S)         | L → T → food; L → T              | L → T → food; L                              | L → food                           |

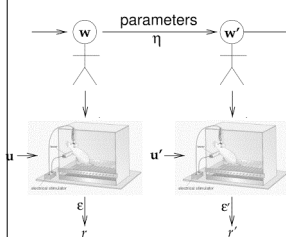


(Bucci, Holland, & Gallagher, 1998)

## Pavlovian Conditioning

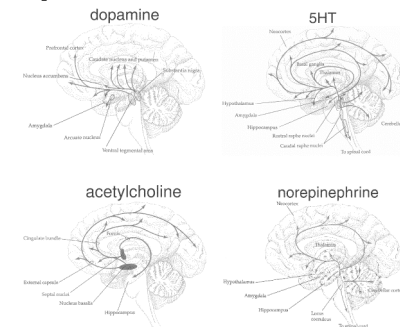
- evolutionary prior
  - amoebae don't learn to absorb food!
- Pavlovian/instrumental competition
  - +ve : negative automaintenance; chicks in a looking glass world
  - ve : depressive realism

## Conditioning



- output model
  - striatum/PFC?
- update model
  - unexpected uncertainty for change: (NE)
  - uncertainty-dependent learning rates: (ACh)
  - backwards blocking: (?)
- decision model
  - action system competition: (ACh?)
  - reinforcement learning (DA, 5HT)

## Computational Neuromodulation



- general: excitability, signal/noise ratios
- specific: prediction errors, uncertainty signals