

Neuromodulators and the Neural Representation of Uncertainty

Peter Dayan

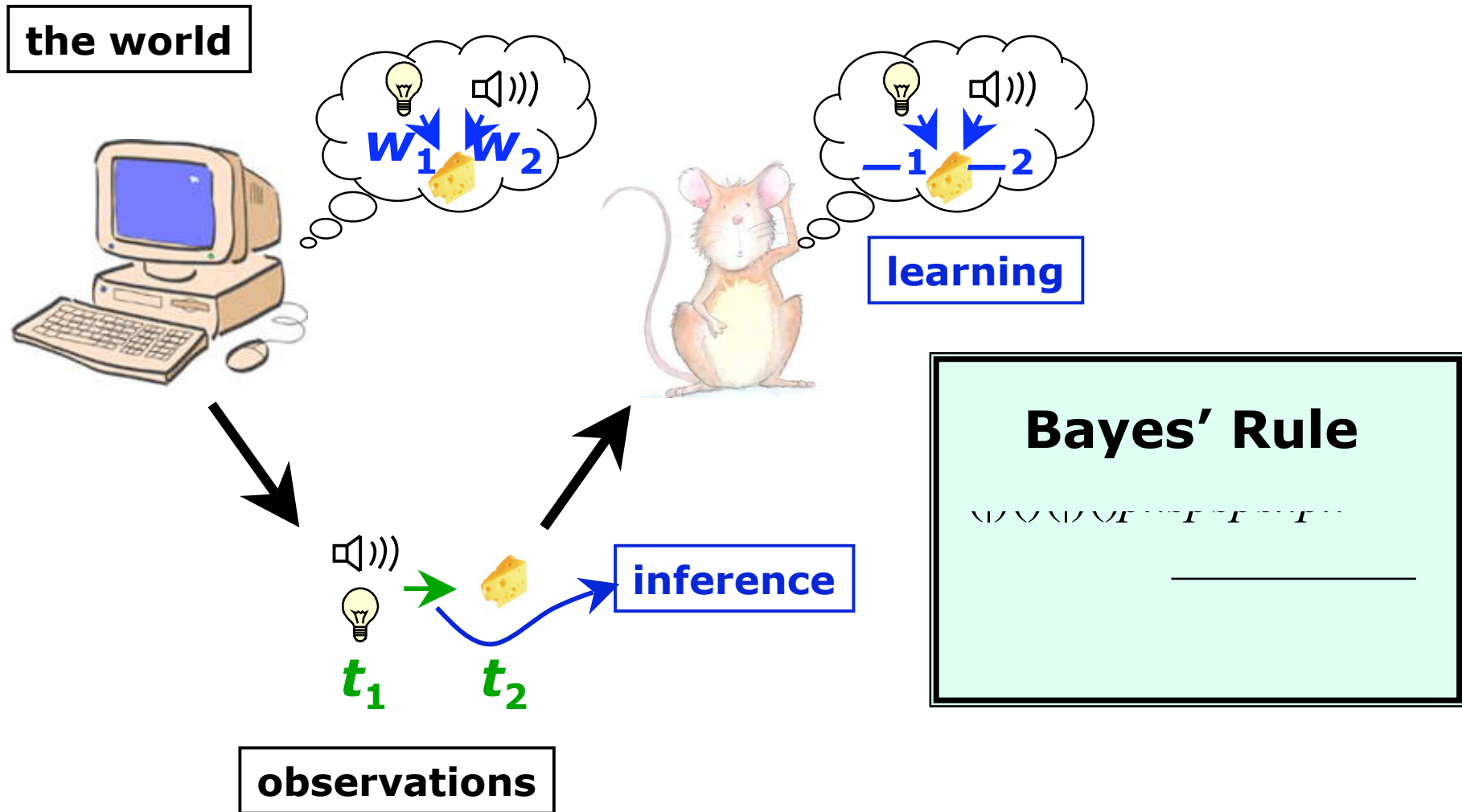
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Computational Neuromodulation

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

Learning and Inference



Bayesian Uncertainty

- **arises** from:
 - stochasticity
 - ignorance
 - transient
 - possibility of ongoing change
- **affects**:
 - learning (the **more** the merrier)
 - inference (the **less** the merrier)

Experimental Data

ACh & **NE** have similar *physiological* effects

- *suppress* recurrent & feedback processing
(e.g. Kimura *et al*, 1995; Kobayashi *et al*, 2000)
- *enhance* thalamocortical transmission
(e.g. Gil *et al*, 1997)
- *boost* experience-dependent plasticity
(e.g. Bear; Shulz; Merzench)

ACh & **NE** have distinct *behavioral* effects:

- **ACh** *boosts* learning to stimuli with uncertain consequences
(e.g. Bucci, Holland, & Gallagher, 1998)
- **NE** *boosts* learning upon encountering global changes in the environment
(e.g. Devauges & Sara, 1990)

Learning

- Learning: predict; control

$\Delta \text{ weight } \alpha (\text{error}) \times (\text{learning rate}) \times (\text{stimulus})$

- dopamine

phasic prediction error for future reward

- serotonin

phasic prediction error for future punishment

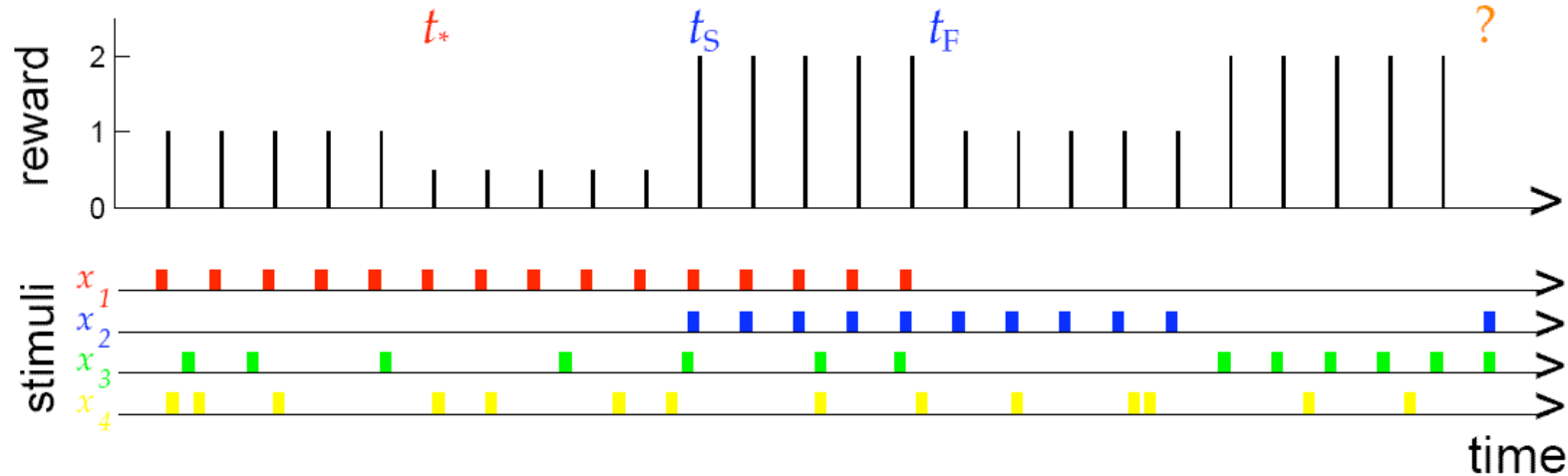
- acetylcholine

expected uncertainty boosts learning

- norepinephrine

unexpected uncertainty boosts learning

Conditioning



reward given

$$r = \mathbf{w} \cdot \mathbf{x} + \epsilon$$

prediction weights

$$\mathbf{w}' = \mathbf{w} + \eta$$

where

output noise

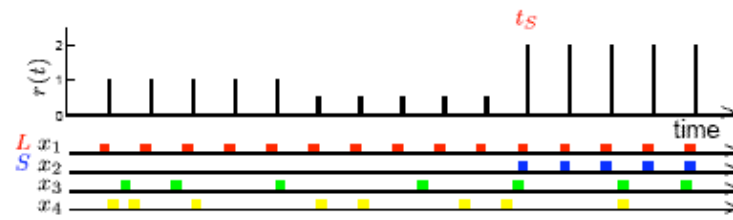
$$\epsilon \sim N[0, \rho^2]$$

allowable drift

$$\eta \sim N[0, \sigma^2 \mathbf{I}]$$

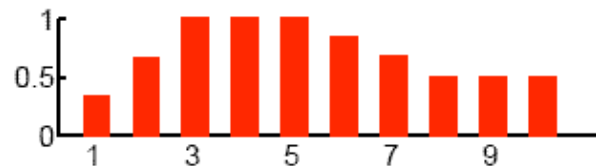
Single Stimulus

Intuition

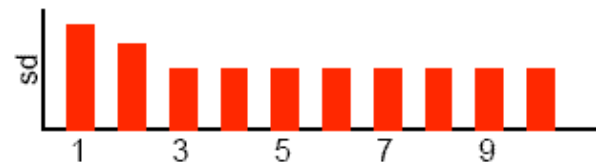


window model: w_L is the average of last three rewards:

mean goes like

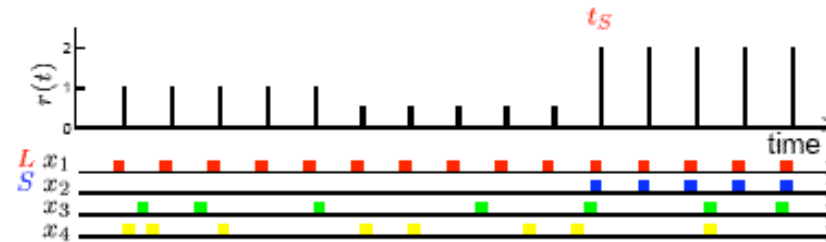


standard deviation goes like



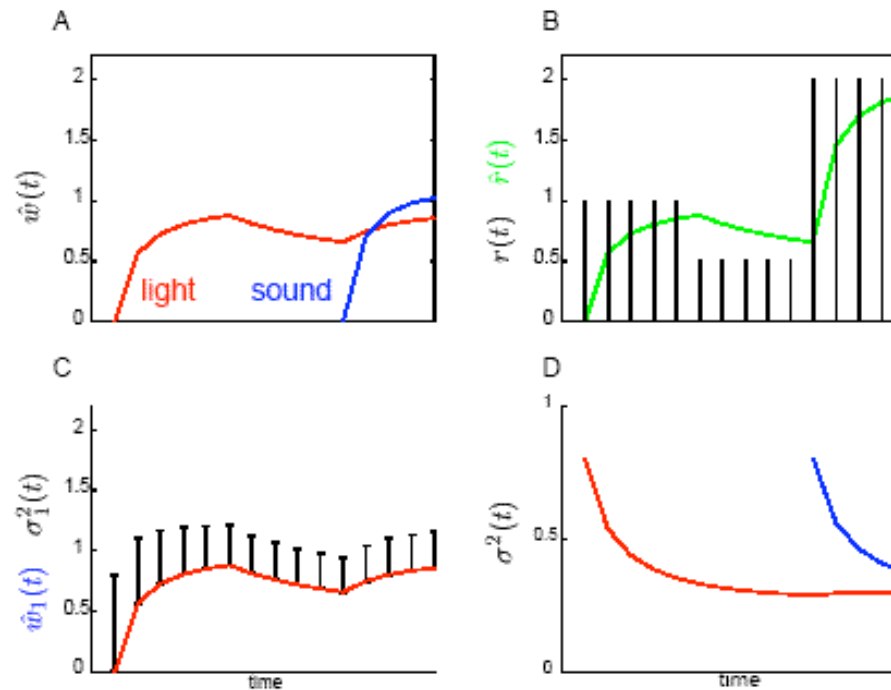
- more data \Rightarrow more certain
- use of 3 rewards controls speed of adaptation
- asymptotic sd shouldn't ignore **changes** in r

Multiple Stimuli



Competition for prediction error between L and S:

sound should 'win' since less well established



Formally: Kalman Filter

$$\begin{aligned} \text{observation: } r &= \mathbf{w} \cdot \mathbf{x} + \epsilon \\ \text{state: } \mathbf{w}' &= \mathbf{w} + \eta \end{aligned}$$

$$\mathbf{w} \sim N[\hat{\mathbf{w}}, \Sigma]$$

$$\delta = r - \hat{\mathbf{w}} \cdot \mathbf{x}$$

$$\hat{\mathbf{w}}' = \hat{\mathbf{w}} + \delta \frac{\Sigma \cdot \mathbf{x}}{\rho^2 + \mathbf{x} \cdot \Sigma \cdot \mathbf{x}}$$

$$(\mathbf{w}' = \mathbf{w} + \delta \alpha \mathbf{x} \quad \text{delta rule})$$

- like the **delta** rule, bar compression and rotation
- **compression** is competition for learning

$$\Sigma_{ii} / (\rho^2 + \sum_j \Sigma_{jj})$$

- ρ^2 sets learning rate according to noise (KKT)
- **rotation** allows backwards blocking
- update for Σ

$$\Sigma' = \Sigma + \sigma^2 \mathbb{I} - \frac{\Sigma \cdot \mathbf{x} \cdot \mathbf{x} \cdot \Sigma}{\rho^2 + \mathbf{x} \cdot \Sigma \cdot \mathbf{x}}$$

Δ weight α (**error**) x (**learning rate**) x (stimulus)

ACh and Learning

- Holland; Gallagher showed

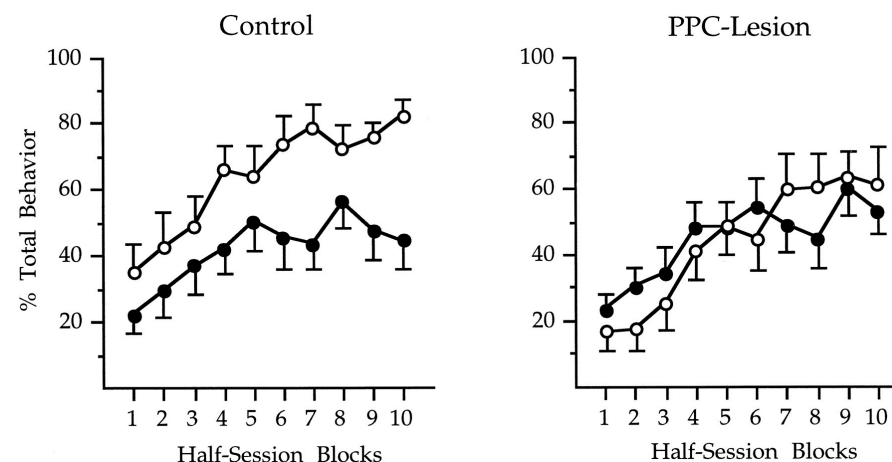


to be critically involved in boosted learning

- hippocampal/ACC ACh involved in suppressed learning

Table 1. Outline of procedures for Experiment 1

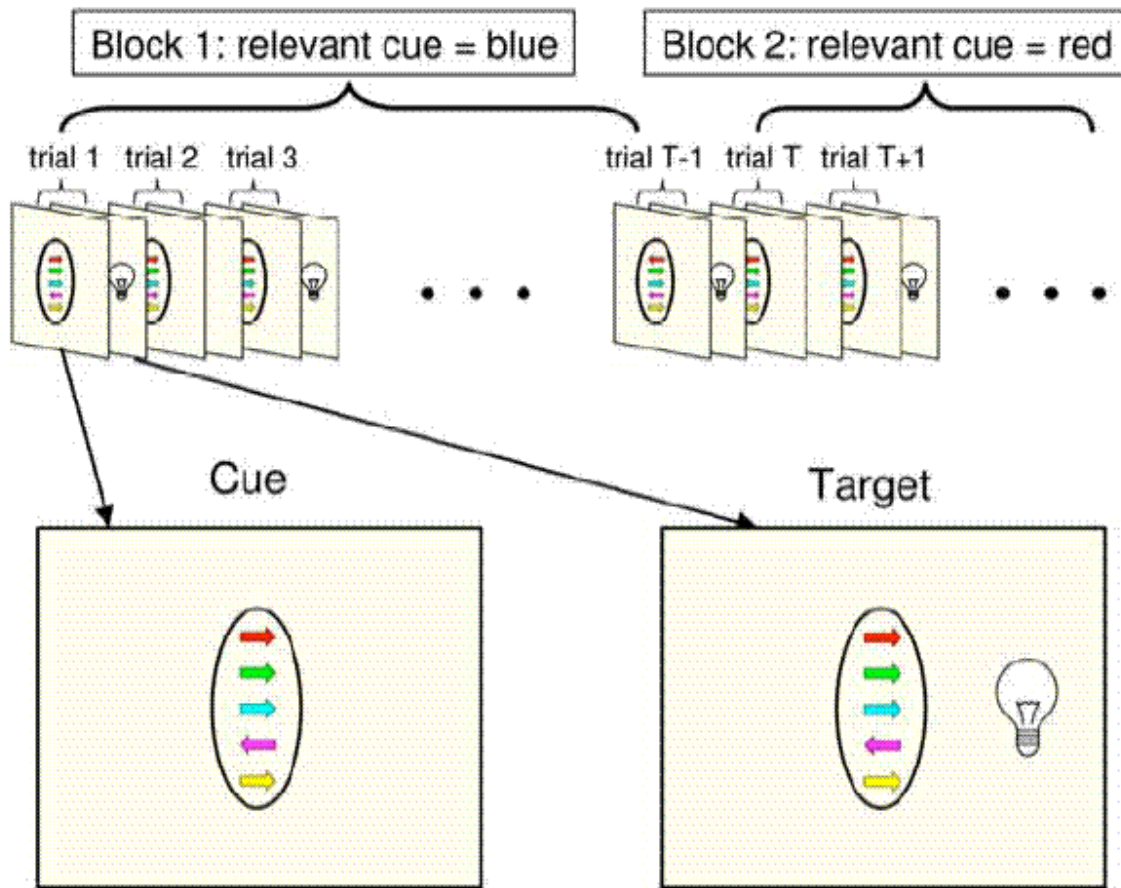
Treatment condition (groups)	Phase 1: consistent L-T relation	Phase 2: experimental change in L-T relation	Phase 3: test of conditioning to L
Consistent (CTL-C, PPC-C)	L \rightarrow T \rightarrow food; L \rightarrow T	L \rightarrow T \rightarrow food; L \rightarrow T	L \rightarrow food
Shift (CTL-S,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



(Bucci, Holland, & Gallagher, 1998)

expected uncertainty

Learning and Inference



- Posner task with unsignalled cue/validity changes

ACh

- `Reversal' task with stable validities

NE

Formal Framework

NE

ACh

variability in **identity** of relevant cue

variability in **quality** of relevant cue

$$1 - \lambda_t^*$$

$$1 - \gamma_t^*$$

cues: vestibular, visual, ...

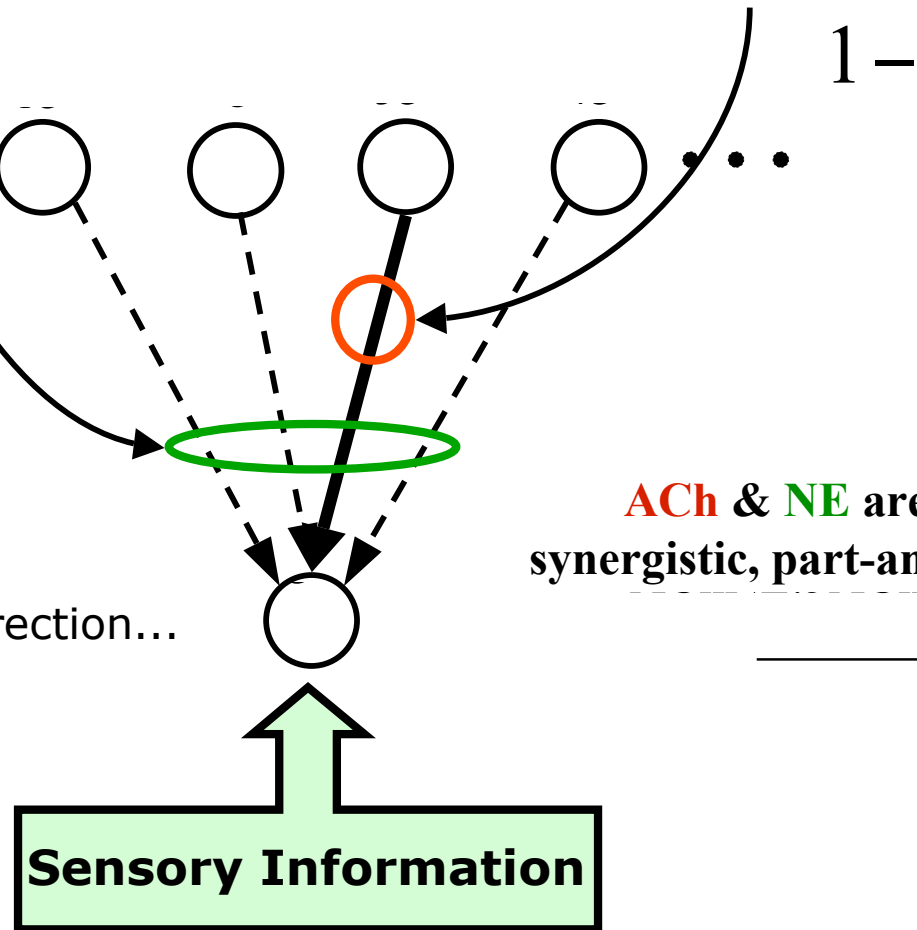
$$\mu_t^* = i$$

$$P^*(\mu_t^* | D_t) = \lambda_t^*$$

$$P^*(\mu_t = j \neq i | D_t) = \frac{1 - \lambda_t^*}{h - 1}$$

target: stimulus location, exit direction...

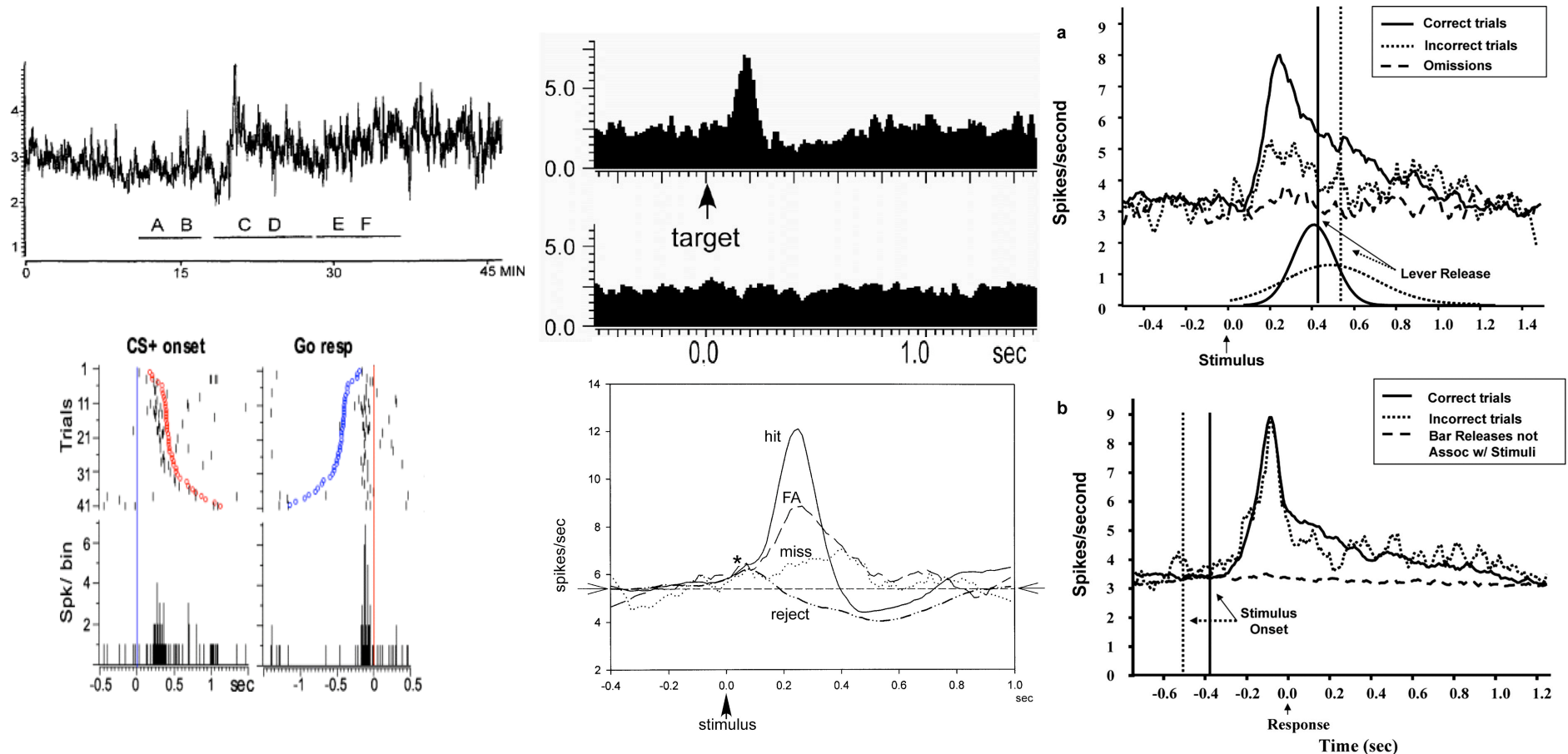
avoid representing
full uncertainty



ACh & NE are part-synergistic, part-antagonistic:

Phasic NE: A-J; Sara

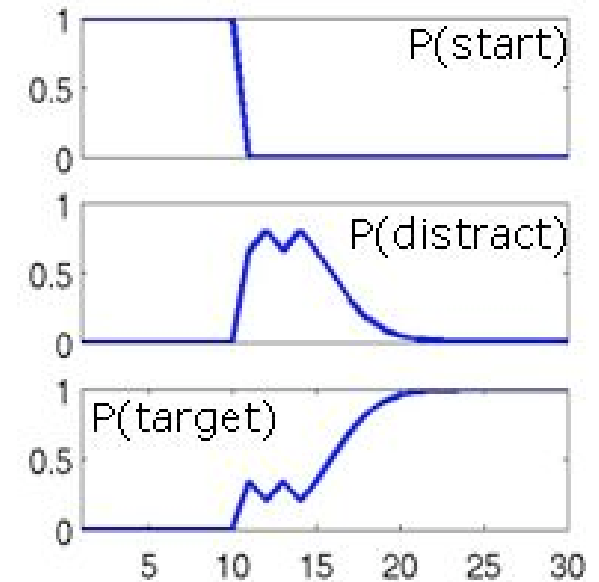
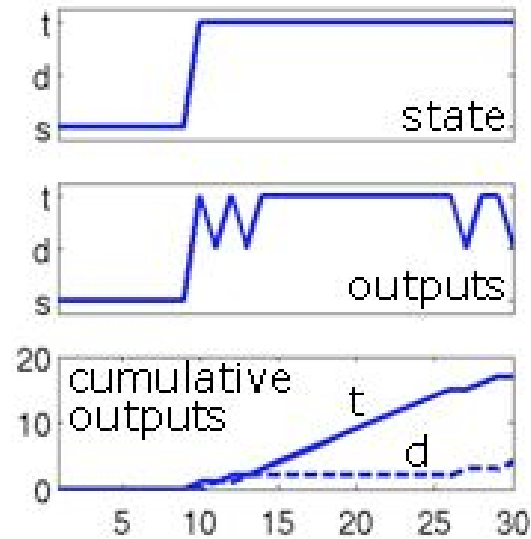
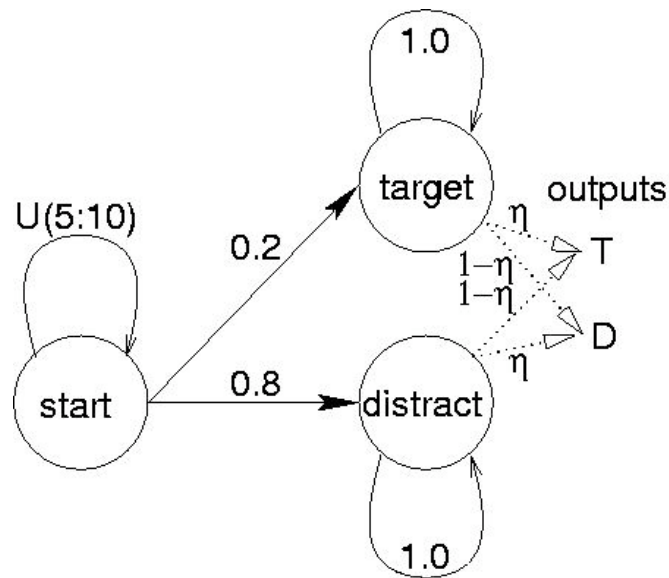
detect and react to a **rare** target amongst **common** distractors



- elevated tonic activity for reversal
- activated by **rare** target (and reverses)
- not reward/stimulus related? more response related?

Clayton, *et al*

Vigilance Model



- variable time in start
- η controls confusability

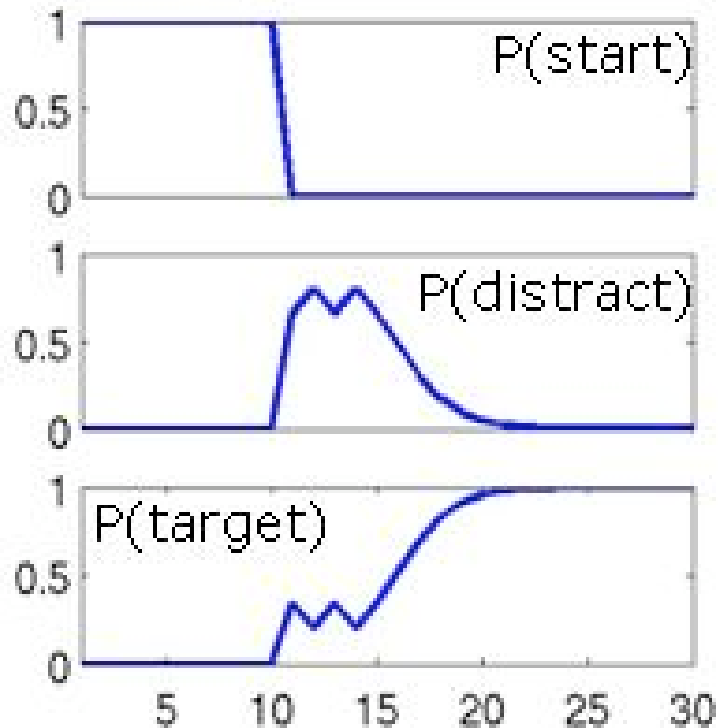
- one single run
- cumulative is clearer

- exact inference
- effect of 80% prior

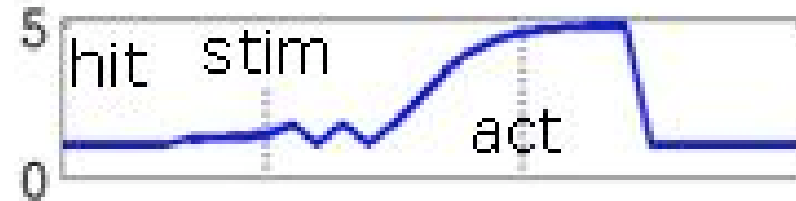
Phasic NE

- NE reports **uncertainty** about current state
 - state in the **model**, not state of the model
 - **divisively** related to prior probability of that state
- NE measured relative to **default state sequence**
start _ distractor
- **temporal** aspect - **start _ distractor**
- **structural** aspect target *versus* distractor

Phasic NE

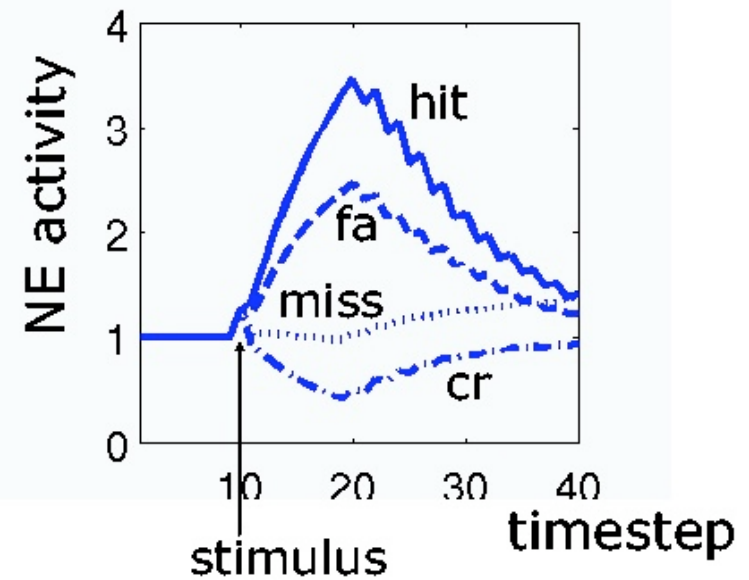
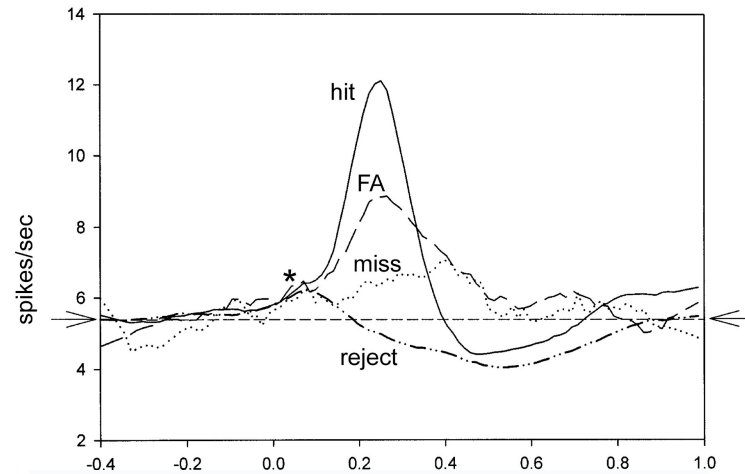
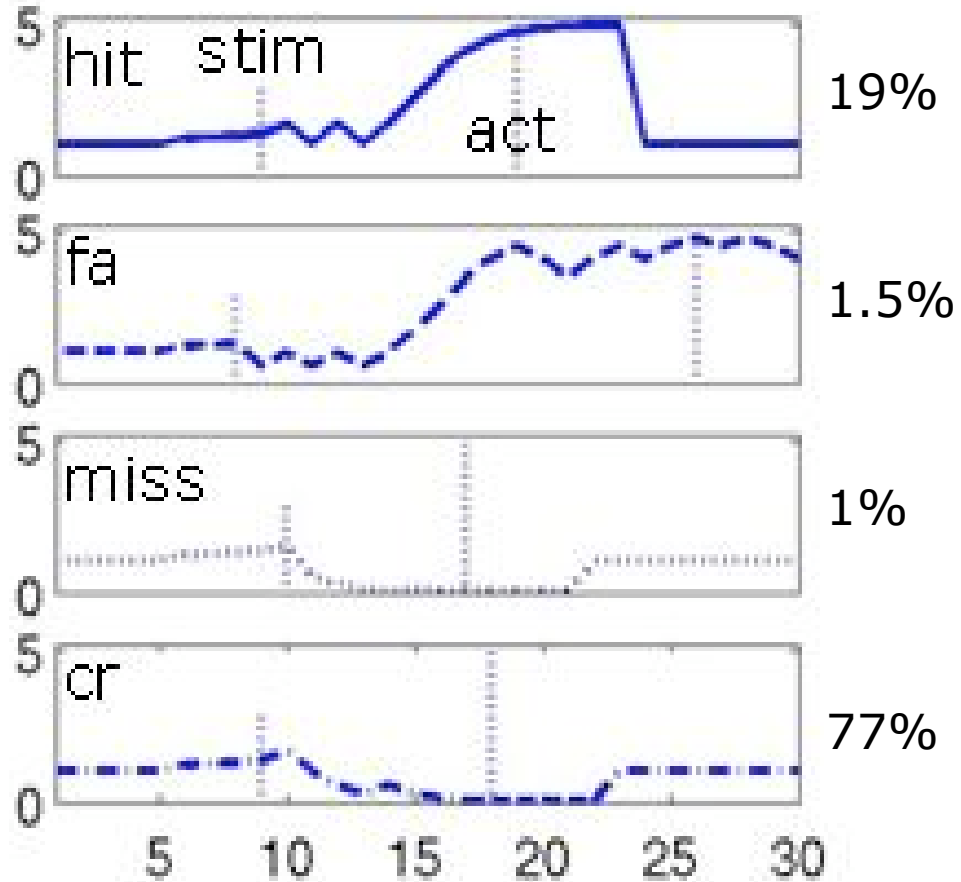


(small prob of reflexive action)



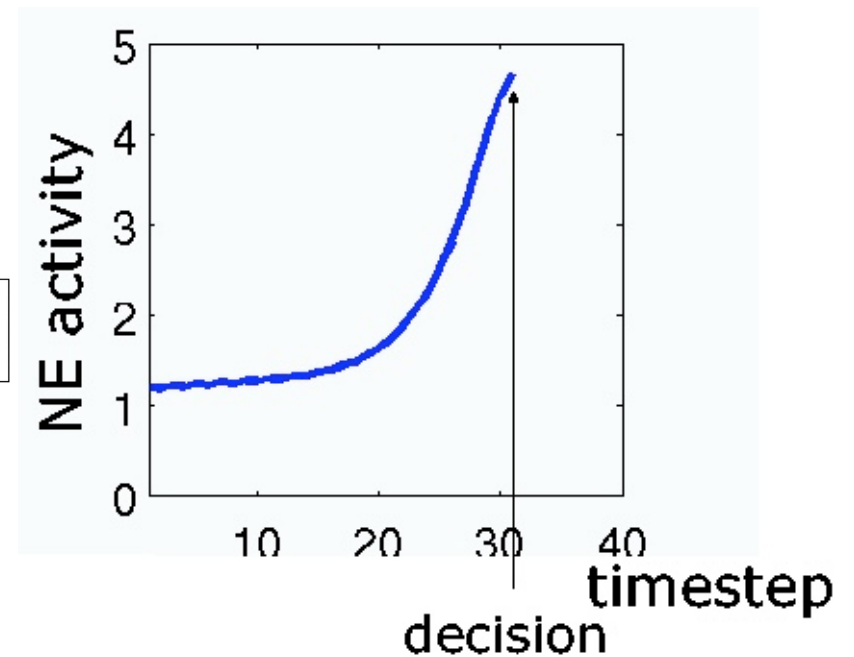
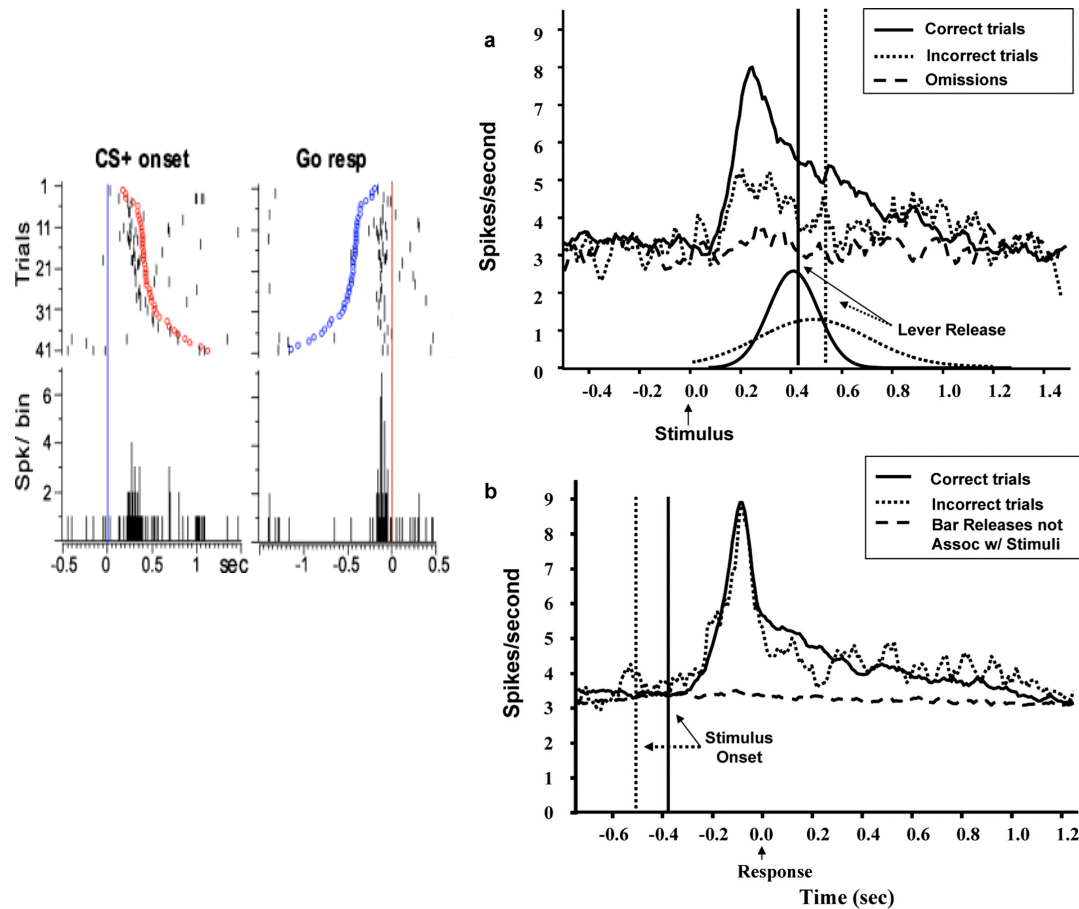
- onset response from timing uncertainty (SET)
- growth as $P(\text{target})/0.2$ rises
- act when $P(\text{target})=0.95$
- stop if $P(\text{target})=0.01$
- arbitrarily set $NE=0$ after 5 timesteps

Four Types of Trial



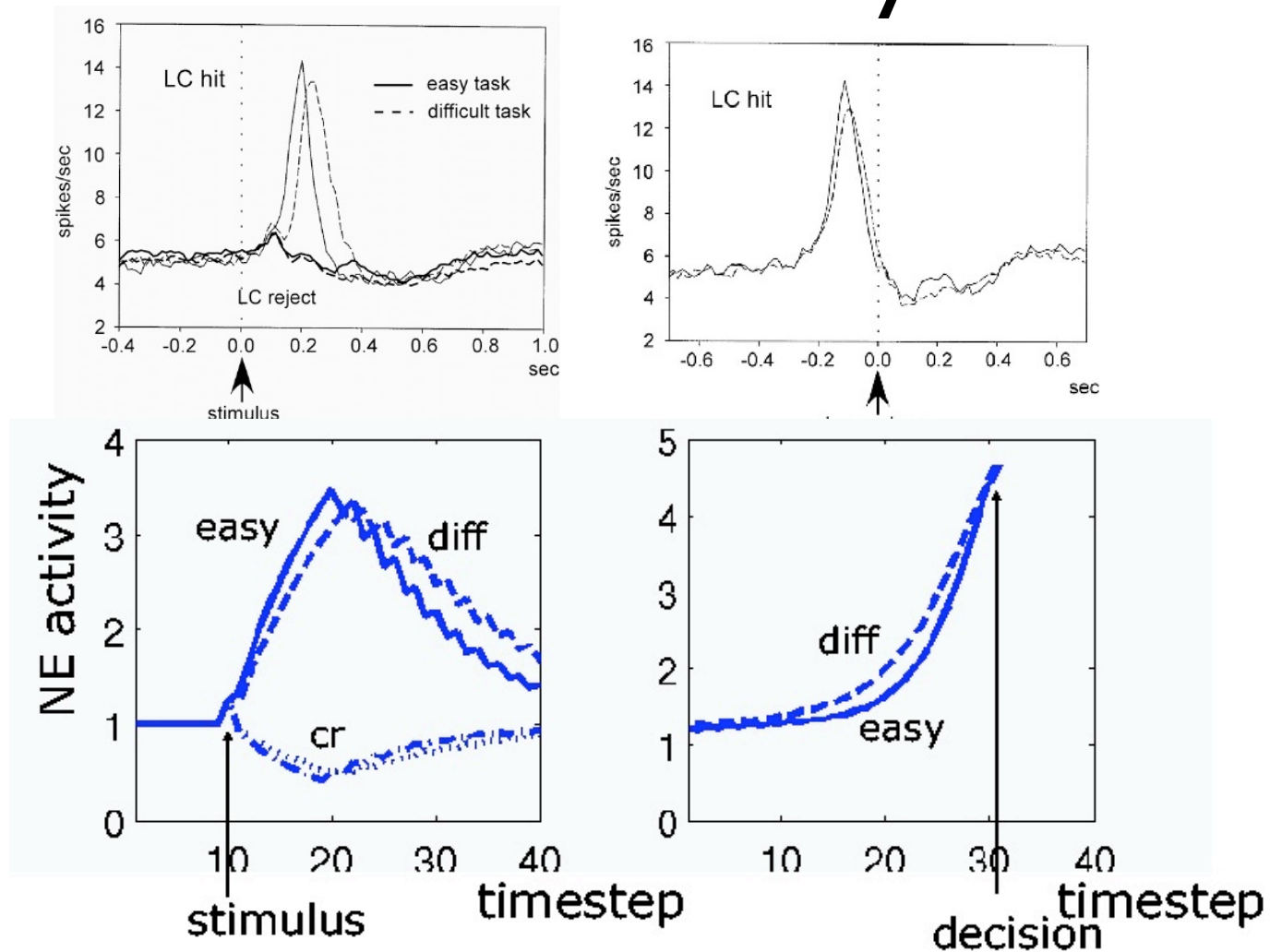
fall is rather arbitrary 18

Response Locking



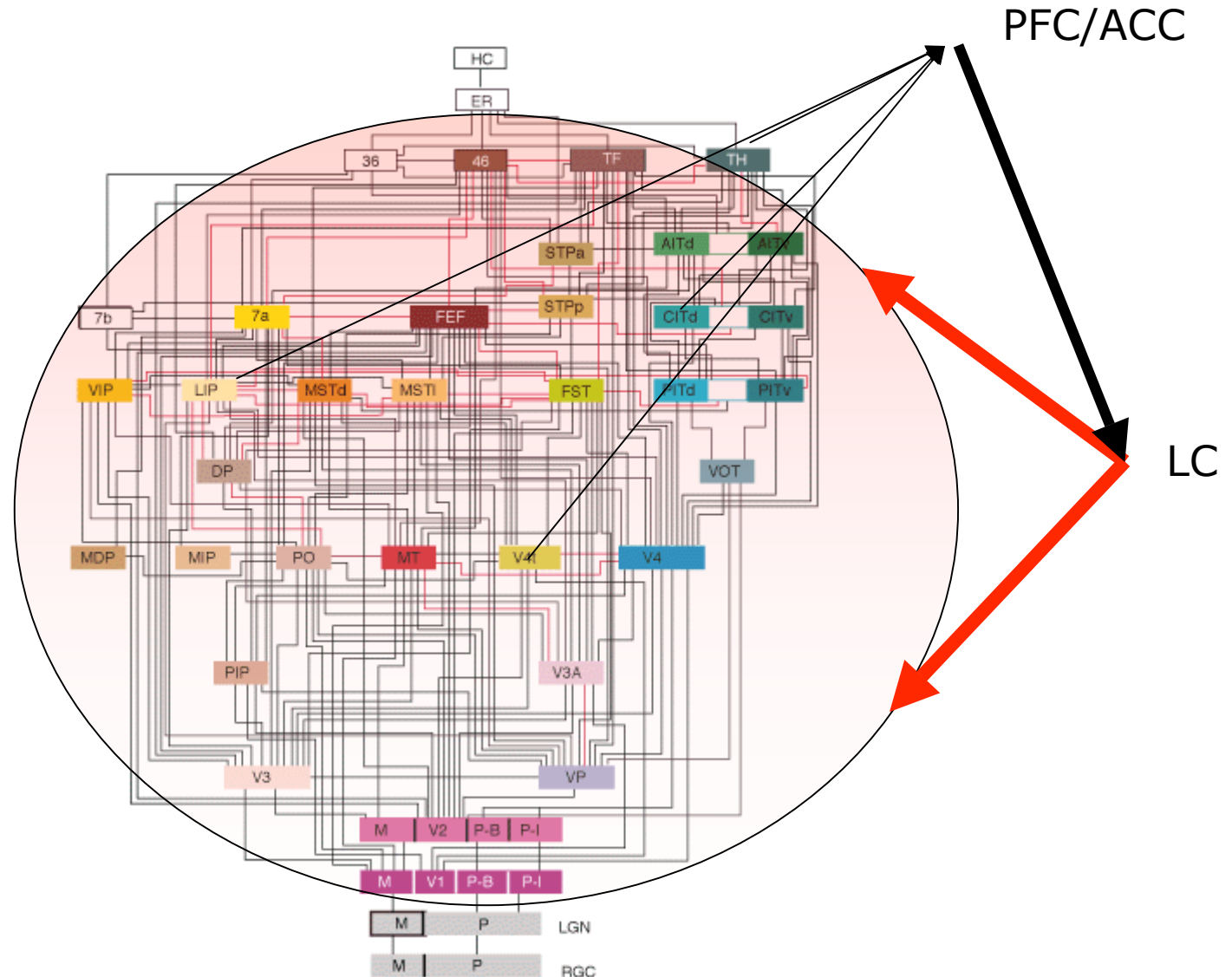
slightly flatters the model – since no further response variability

Task Difficulty



- set $_ = 0.65$ rather than 0.675
- information accumulates over a longer period
- hits more affected than cr's
- timing not quite right

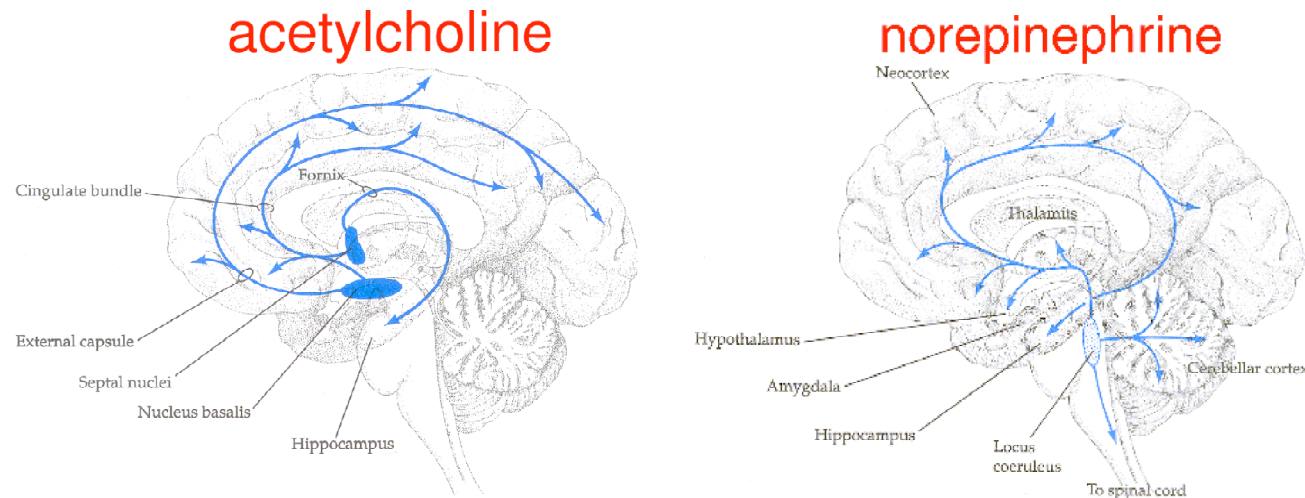
Interrupts/Reset (Shulz)



Discussion

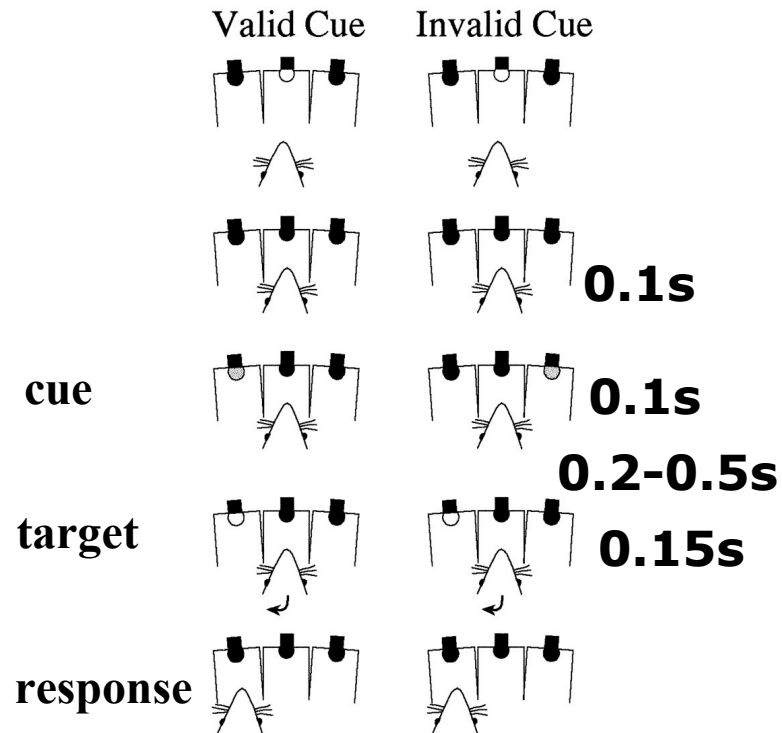
- phasic NE as unexpected state change *within* a model
- **relative** to prior probability; **against** default
- **interrupts** ongoing processing
- tie to ADHD?
- close to **alerting** (AJ) – but not necessarily tied to behavioral output (onset rise)
- close to behavioural **switching** (PR) – but not DA
- close to instability (EB)
- phasic ACh: aspects of known variability within a state?

Neuromodulation and Uncertainty

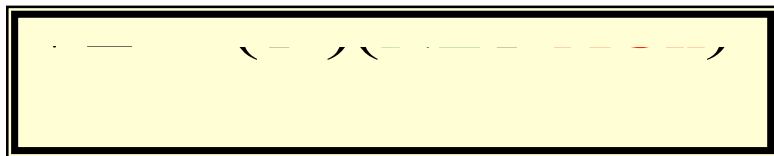


- **ACh/NE** as expected/unexpected uncertainty signals
- experimental psychopharmacological data replicated by simulations
- implications from complex interactions between **ACh** & **NE**
- predictions at the cellular, systems, and behavioral levels
- activity vs weight vs neuromodulatory vs population representations
- irreducible uncertainty vs ignorance

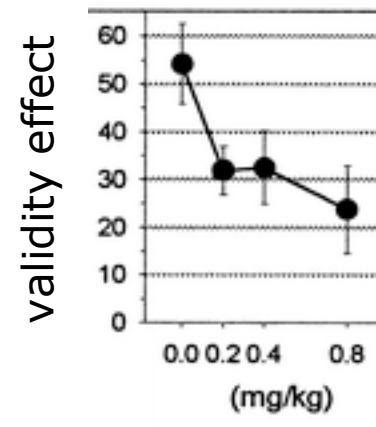
Simulation Results: Posner's Task



no unexpected change



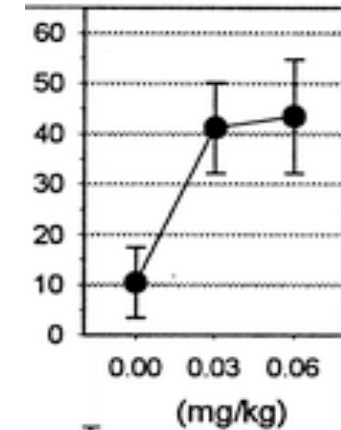
nicotine



concentration

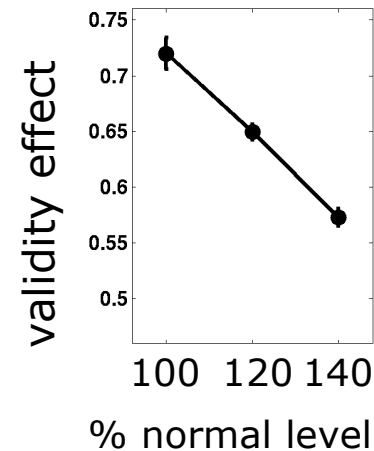
(Phillips, McAlonan, Robb, & Brown, 2000)

scopolamine

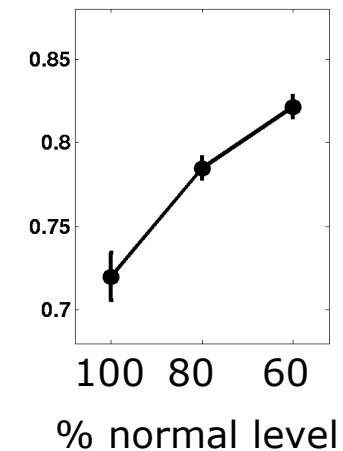


concentration

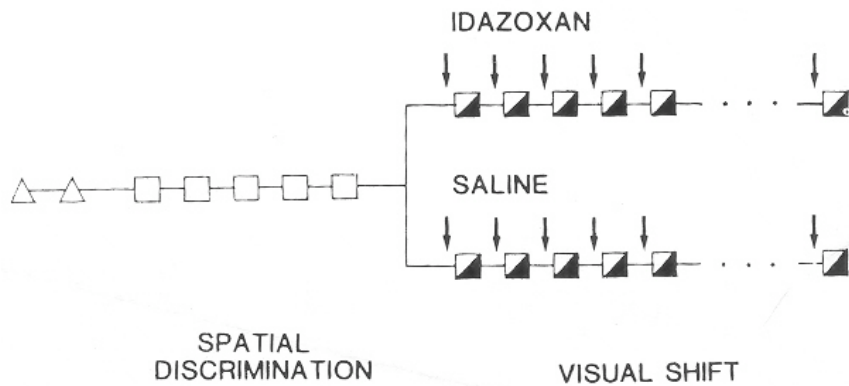
increase ACh



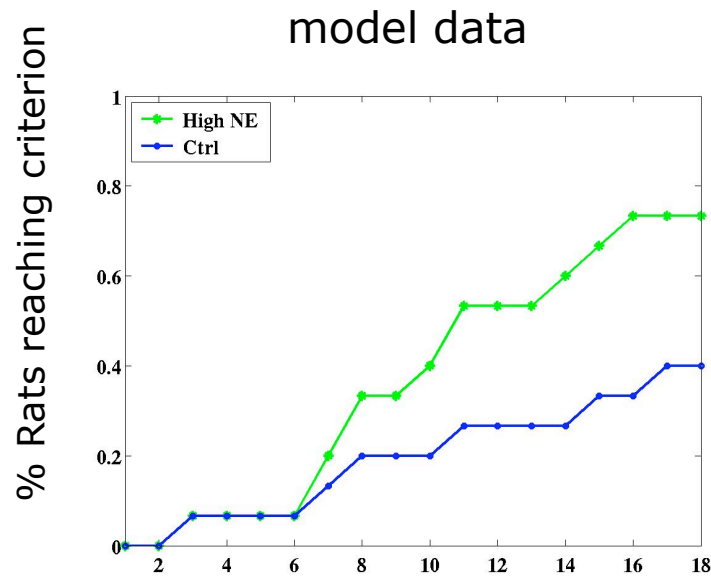
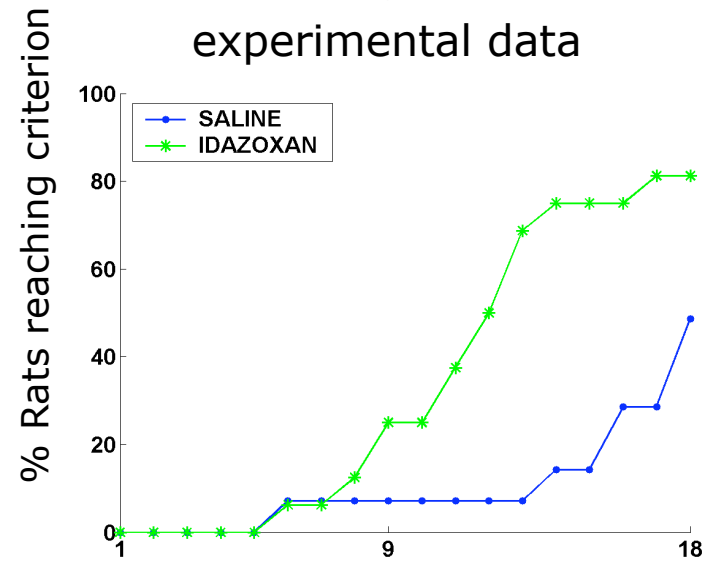
decrease ACh



Simulation Results: Maze Navigation



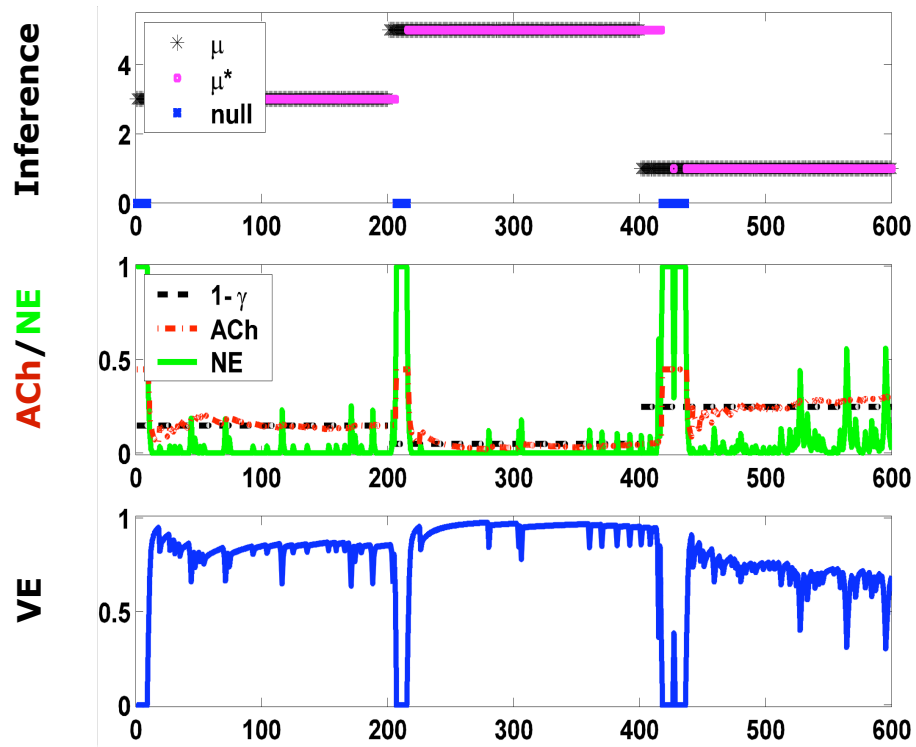
no invalidity



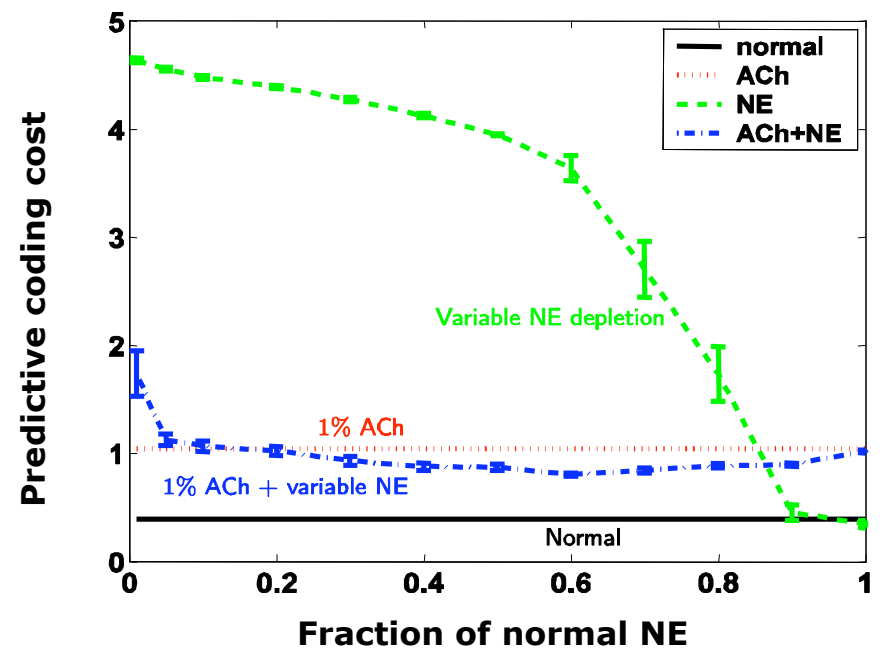
No. days after shift from spatial to visual task
(Devauges & Sara, 1990) 25

ACh/NE

Typical Run



Simulated Pharmacology



Summary

- single framework for understanding ACh, NE and some aspects of attention and learning
- ACh/NE as expected/unexpected uncertainty signals
- experimental psychopharmacological data replicated by model simulations
- implications from complex interactions between ACh & NE
- predictions at the cellular, systems, and behavioral levels
- activity vs weight vs neuromodulatory vs population representations of uncertainty
- Kalman filter; added 'shock' process; also competitive combination
- irreducible uncertainty vs ignorance

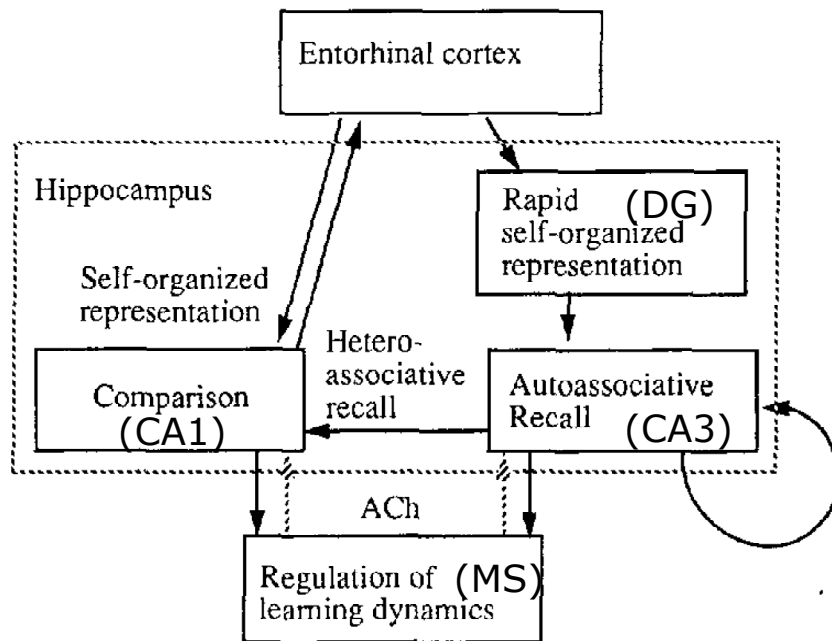
ACh in Hippocampus

Given *unfamiliarity*,

ACh:

- *boosts* bottom-up, *suppresses*

recurrent processing



(Hasselmo, 1995)

ACh in Conditioning

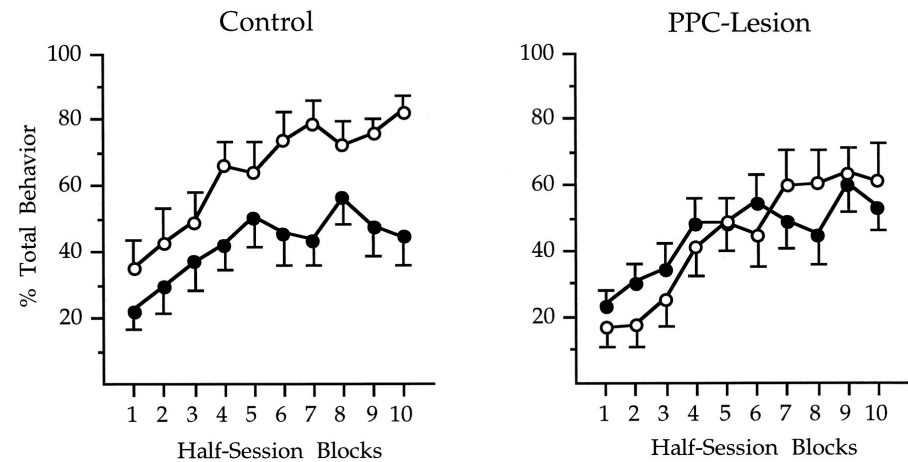
Given *uncertainty*,

ACh:

- *boosts* learning to stimuli of

Table 1. Outline of procedures for Experiment 1

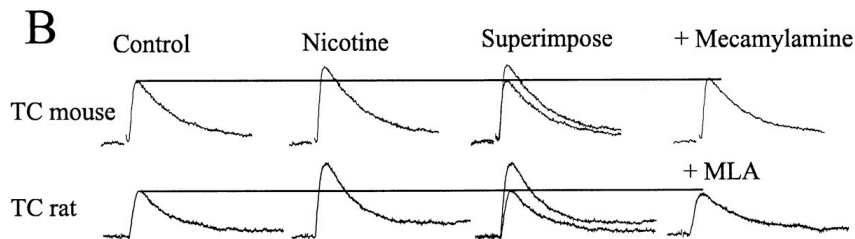
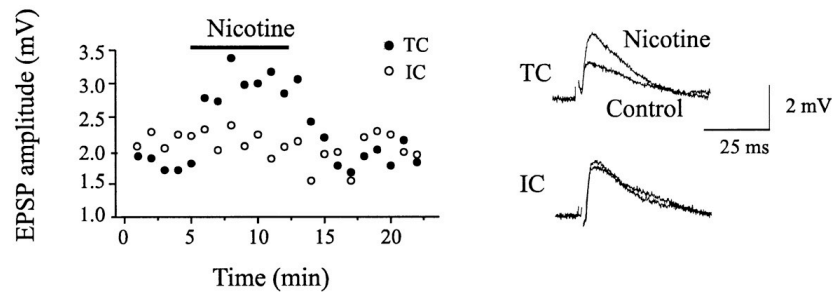
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(Bucci, Holland, & Gallagher, 1998)

Cholinergic Modulation in the Cortex

Electrophysiology Data



(Gil, Connors, & Amitai, 1997)

Examples of Hallucinations Induced by Anticholinergic Chemicals

Scopolamine in normal volunteers	Integrated, realistic hallucinations with familiar objects and faces	Ketchum et al. (1973)
Intravenous atropine in bradycardia	Intense visual hallucinations on eye closure	Fisher (1991)
Local application of scopolamine or atropine eyedrops	Prolonged anticholinergic delirium in normal adults	Tune et al. (1992)
Side effects of motion-sickness drugs (scopolamine)	Adolescents hallucinating and unable to recognize relatives	Wilkinson (1987) Holland (1992)

(Perry & Perry, 1995)

ACh agonists:

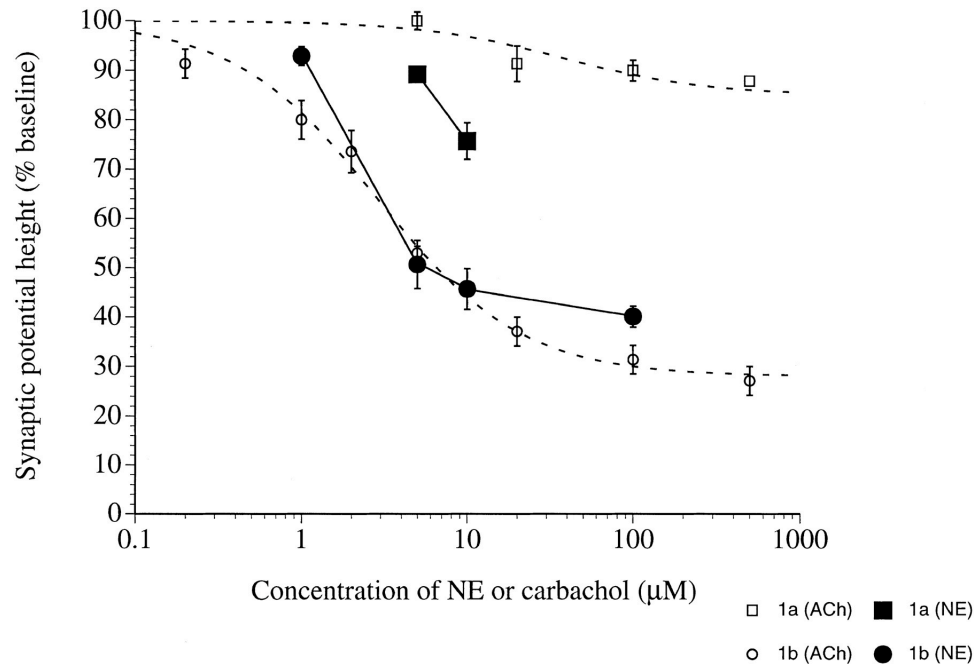
- **facilitate** TC transmission
- **enhance** stimulus-

ACh antagonists:

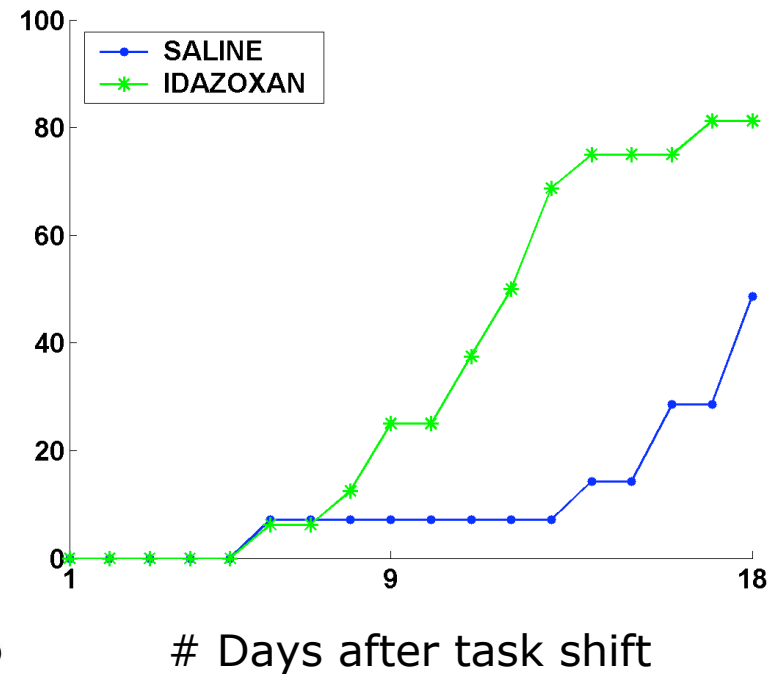
- **induce** hallucinations
- **interfere** with stimulus processing

Norepinephrine

Something similar may be true for NE
(Kasamatsu *et al*, 1981)



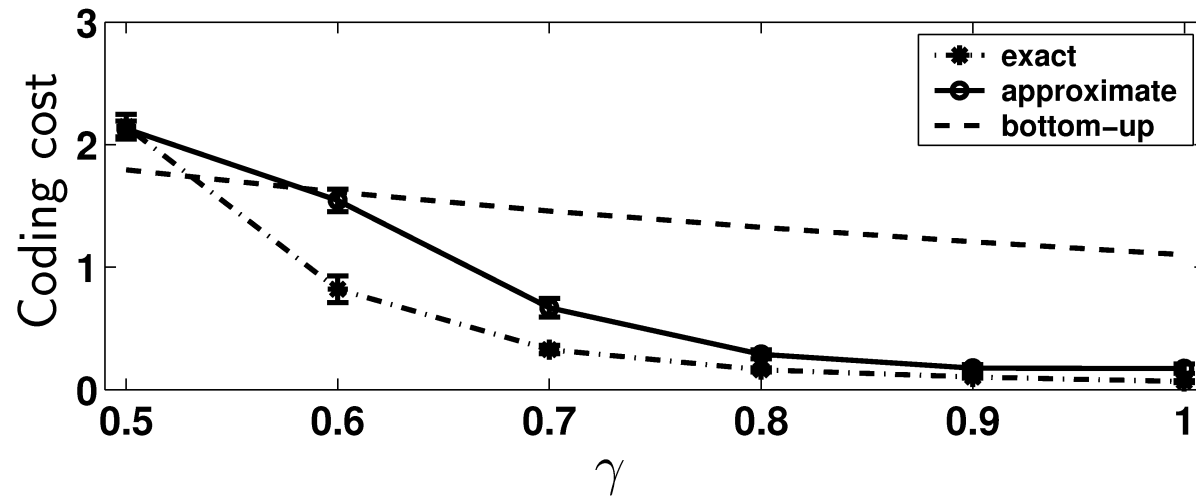
(Hasselmo *et al*, 1997)



(Devauges & Sara, 1990)

NE specially involved in **novelty**, confusing association with attention, vigilance, selective attention

Approximation



approximation is not catastrophic compared with a simpler, algorithm