model-based planning II: mixing memory and desire

ccnss
2018.07.07

slides and references available at

http://aaron.bornstein.org/ccnss/

outline

I. computational role(s) of memories

II. experimental evidence

III. if time: open questions

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uncertainty-based arbitration

- two systems, each useful in different situations

- **model-free**: policies well-learned, cached values highly certain
- **model-based**: state spaces learned, policies and values require evaluation

- … but what about when the state space isn't yet well-learned?

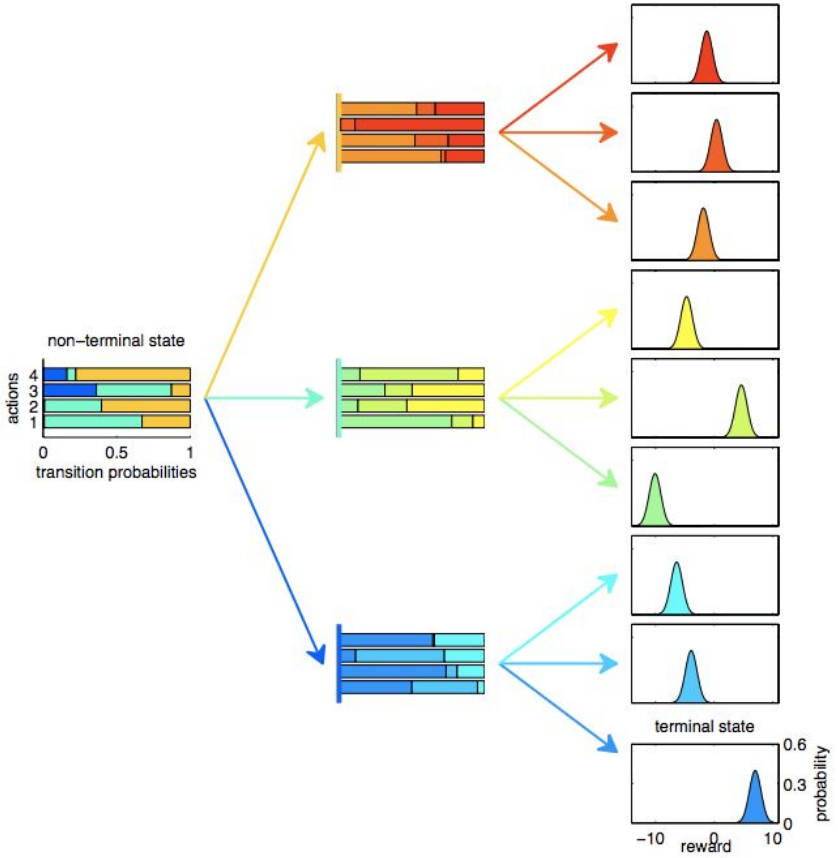
the third way: an “episodic” controller

(lengyel & dayan 2008)

the third way

"tree" MDP (tMDP)
- branching factor B
- depth D

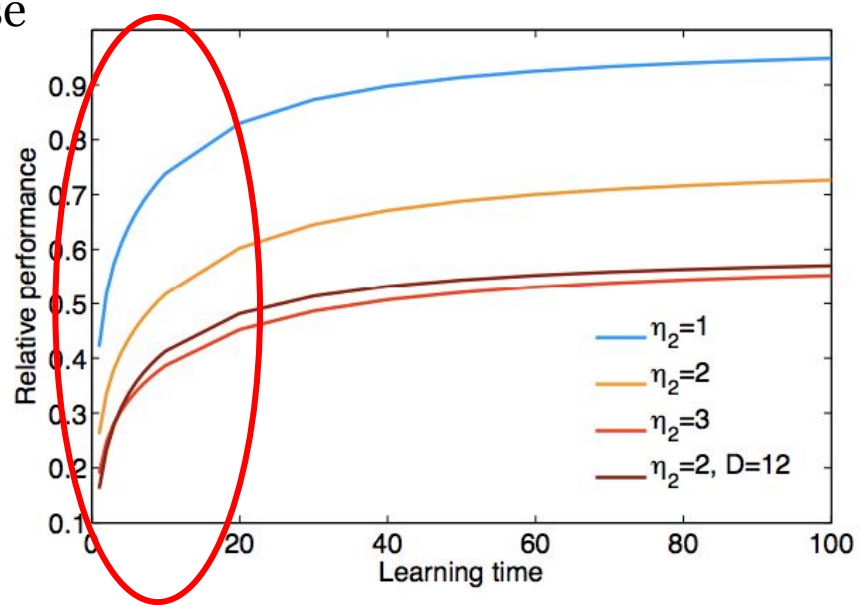
"episode"
- a single trajectory from S_o to terminal



(lengyel & dayan 2008)

model-based performance at noise and complexity

- model-based learning slows with greater noise and/or complexity
  - (*and* is asymptotically lower, hence model-free can come to dominate)



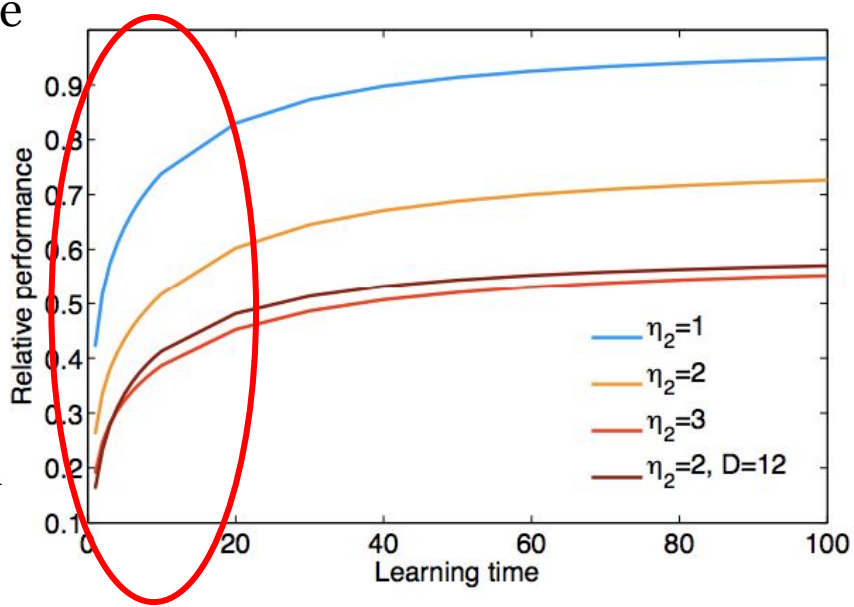
(η = noise, D = depth; relative to perfect "noiseless" performance)

(lengyel & dayan 2008)

model-based performance at noise and complexity

- model-based learning slows with greater noise and/or complexity
  - (*and* is asymptotically lower, hence model-free can come to dominate)

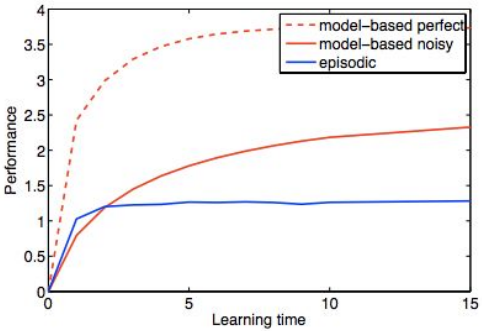
- proposal: "episodic control"
  - sample one previous trajectory, do that.
    - "each time the subject experiences a reward that is … larger than expected … it stores the specific sequence of state-action pairs leading up to this reward, and tries to follow such a sequence whenever it **stumbles upon** a state included in it"
    - "advantages will be ultimately counteracted by the haphazardness of using single samples that are 'adequate', but by that time the other controllers can take over."



(η = noise, D = depth; relative to perfect "noiseless" performance)

(lengyel & dayan 2008)

“episodic control” useful in early learning



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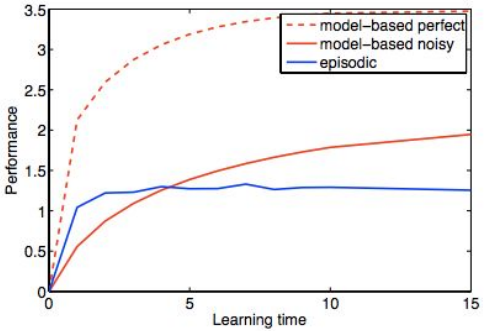

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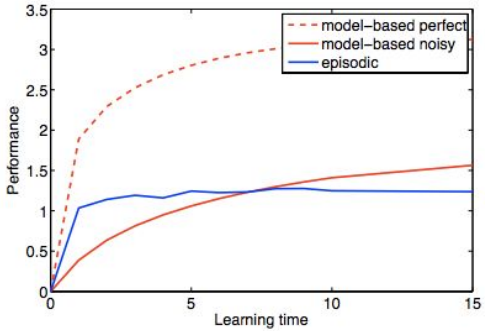


(B=4)

useful early on, but “asymptotic performance of [episodic] is rather poor…”

(lengyel & dayan 2008)

but the world is not a tree mdp

- complexity comes not just from depth and breadth, but also *sparsity*
- generally speaking, we may not be very certain about our current state
- so to use our value function *Q(**S**, A)* it helps to perform *state inference*
- episodic memories can be useful in inferring state when experience is sparse
  - “pattern completion” from “partial input”
  - not just repeating past actions

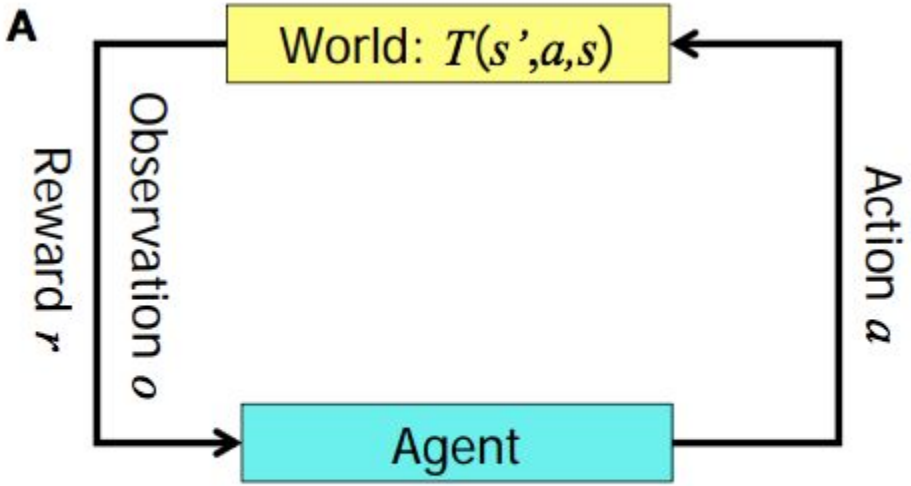
partially observable mdp

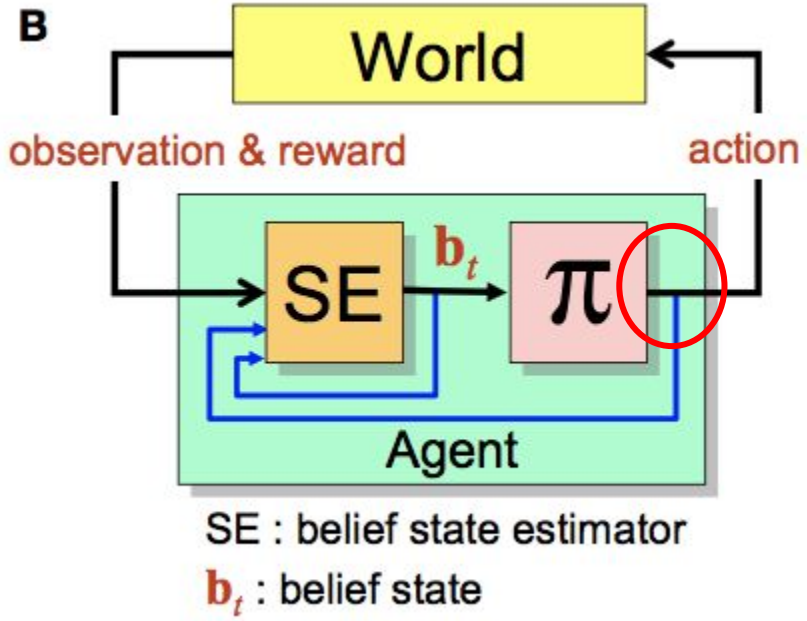
- new state-space formalism: *partially observable* MDP (POMDP)
- rather than fixed *S*, distribution of *beliefs* **b** = *b(S)*, and now Q can be an expectation

$$Q(\mathbf{b}, A) = \mathbb{E}_s \, Q(S, A) b(S)$$

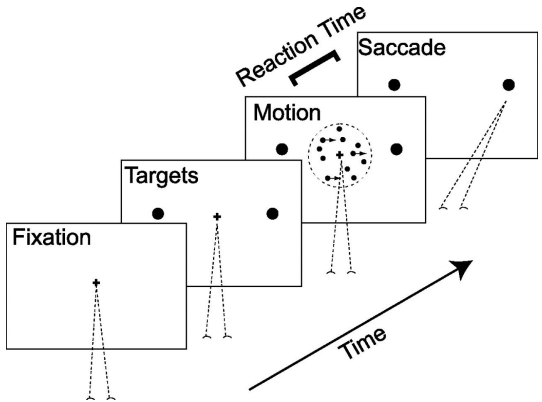
- this carries some degree of uncertainty
- the agent has the option to reduce this uncertainty by *sampling* environment
  - value function is convex in belief — there is always +EV to reducing uncertainty, up to the cost of sampling (e.g. spikes, delaying reward, etc)
  - therefore, sample until the uncertainty is low enough that the cost of sampling (or not-acting) is greater than the cost of acting

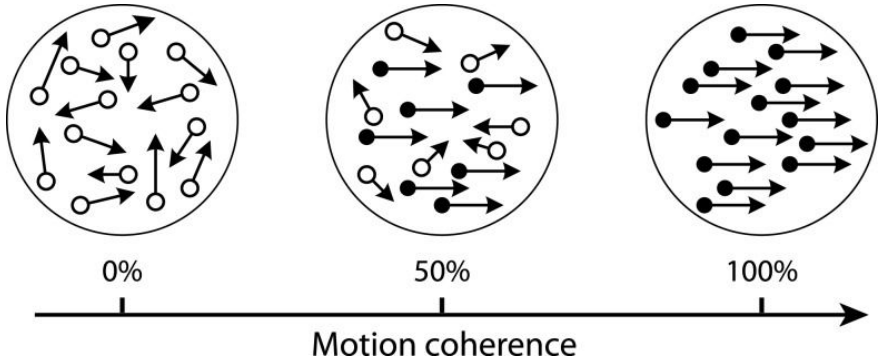
sampling as action



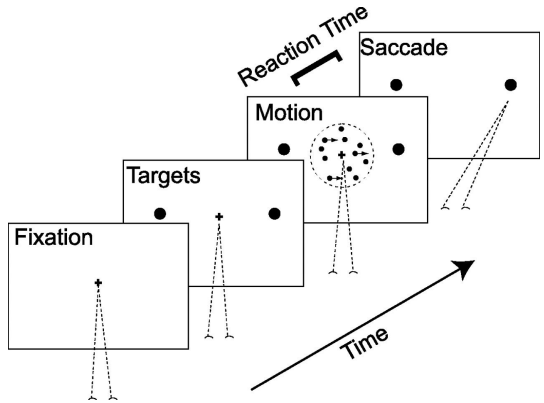


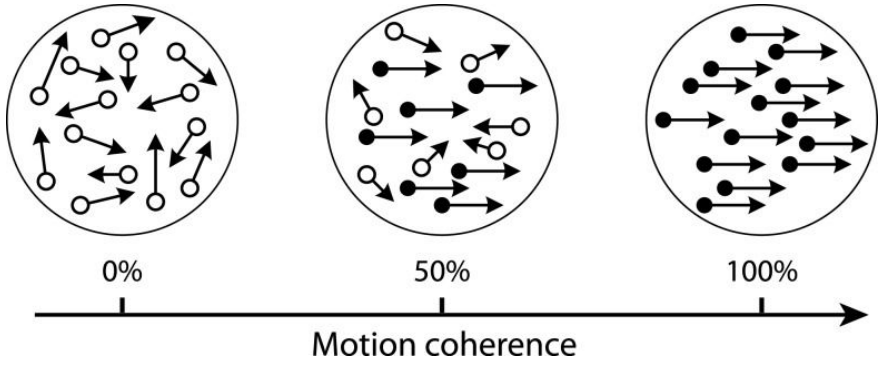
(rao 2010)


Reaction Time
Saccade
Motion
Targets
Fixation
Time


0%
50%
100%
Motion coherence

(rao 2010)

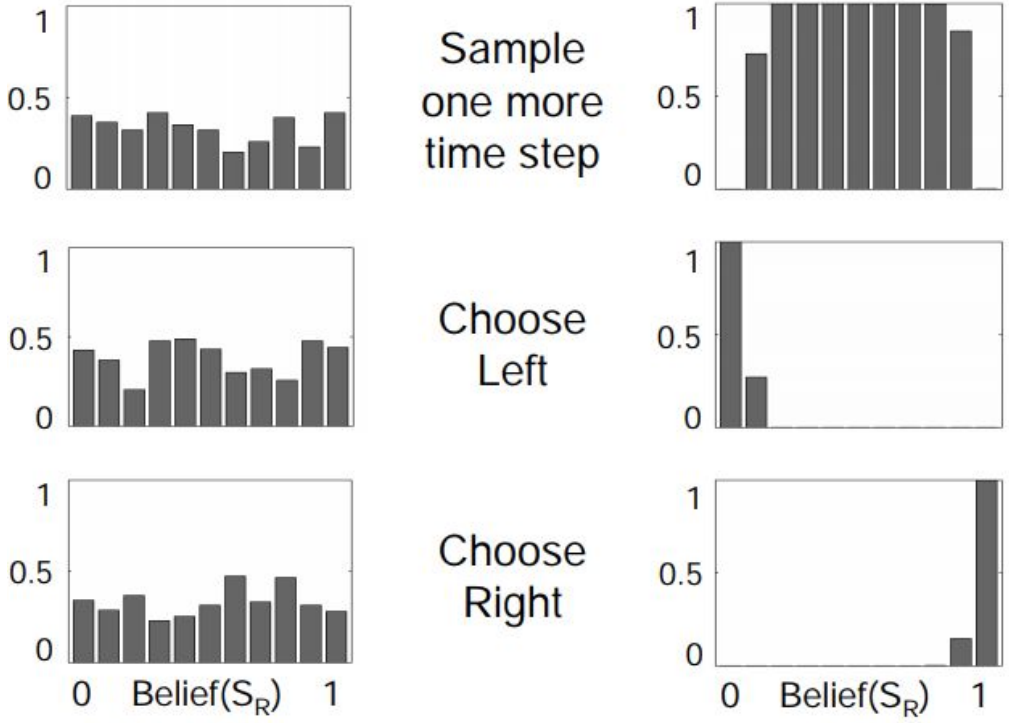




Before Learning

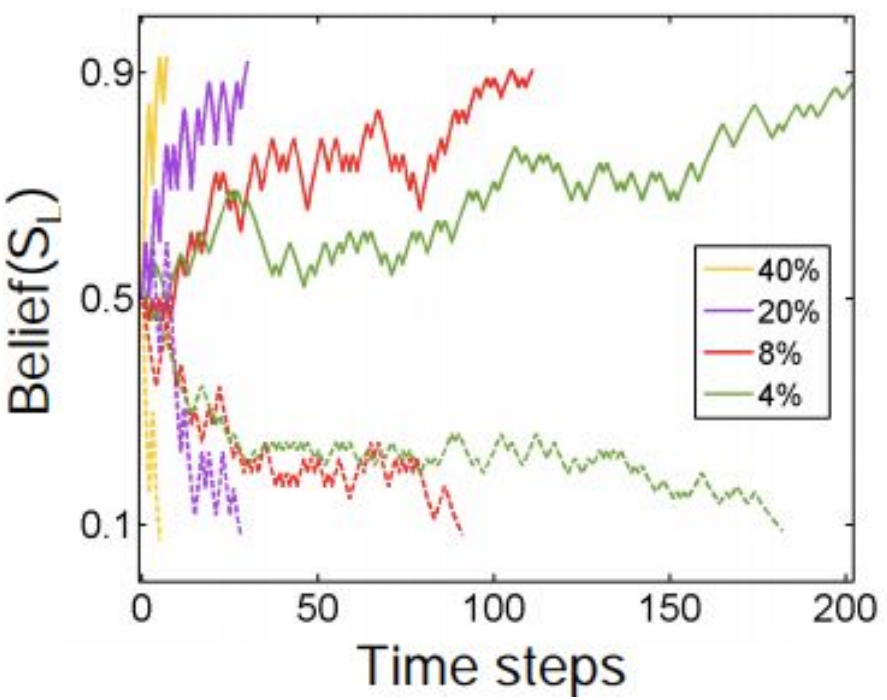
Action

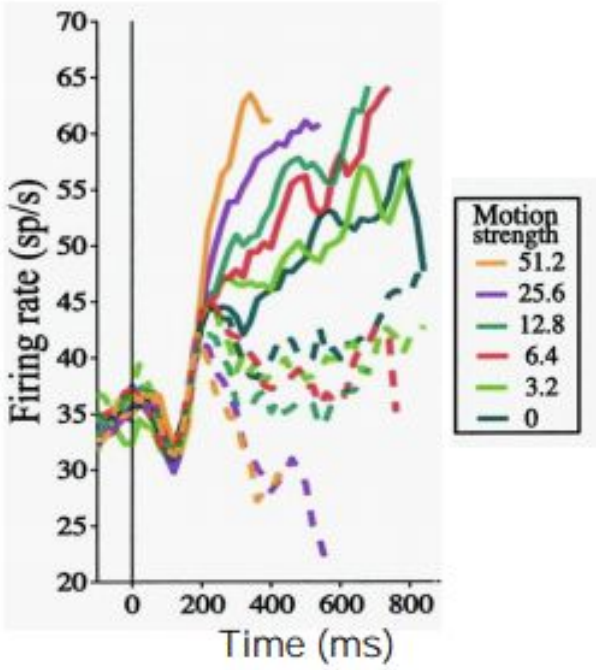
After Learning



(rao 2010)

belief computation matches neural accumulation





(rao 2010)

known unknowns

sampling can resolve two sources of uncertainty

- 1. **estimating** the outcome of an action taken in the current state
- 2. **inferring** the current state

(note: these can be done simultaneously)

this should apply equally to sensory and memory samples, when both can reduce uncertainty about states and actions

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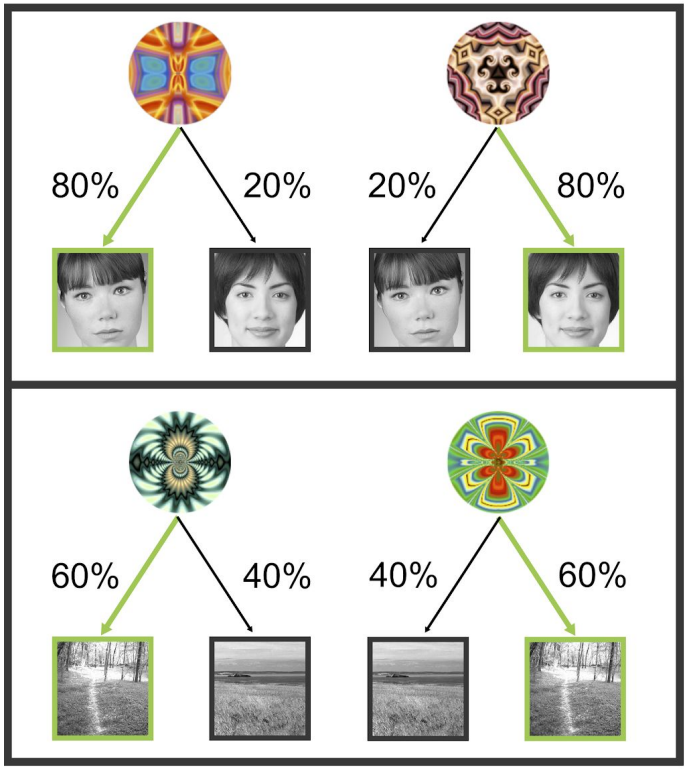
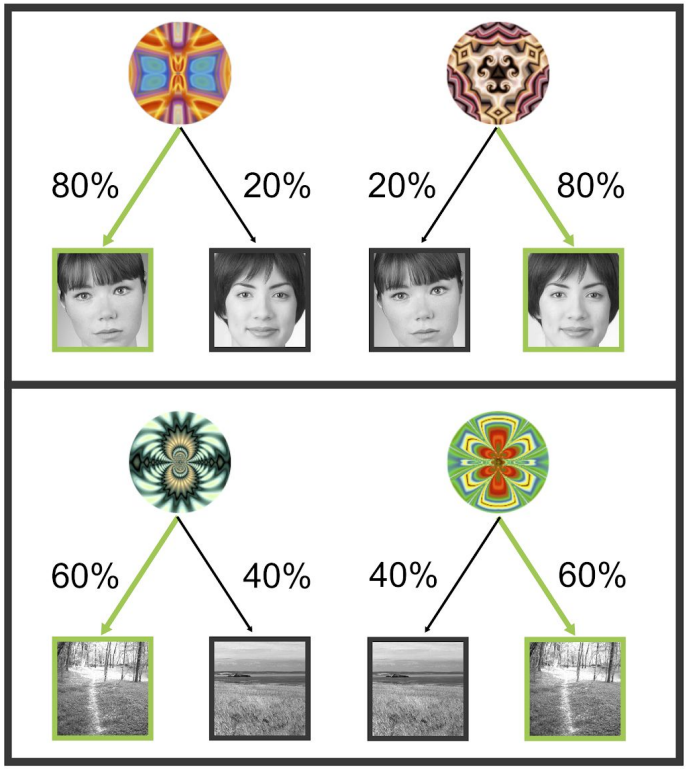
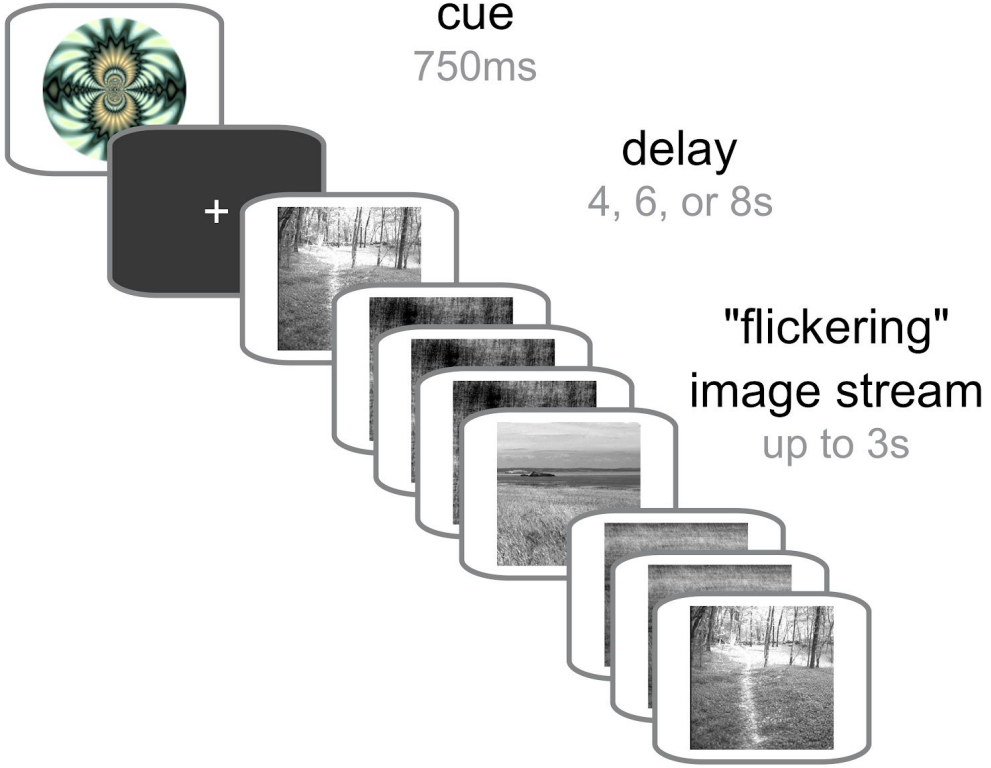
samples from memory reduce state uncertainty



(bornstein et al *under review*)

samples from memory reduce state uncertainty





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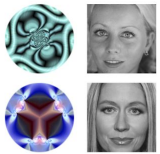
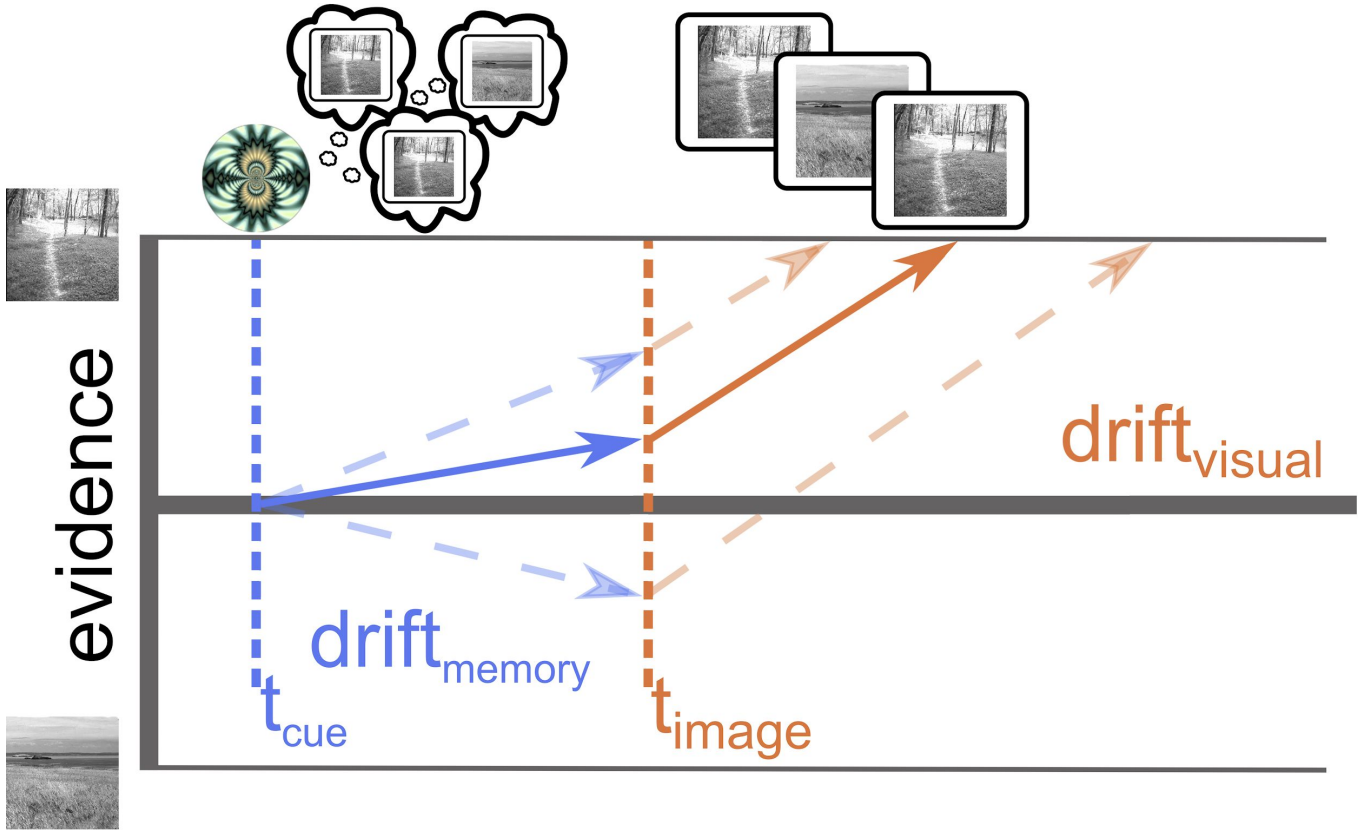
samples from memory reduce state uncertainty

Stimuli	Cue validity	Sensory Evidence
	50%	Strong
	70%	Weak

Stimuli	Cue validity	Sensory Evidence
	80%	Weak
	60%	Strong

(bornstein et al *under review*)

two-stage uncertainty reduction



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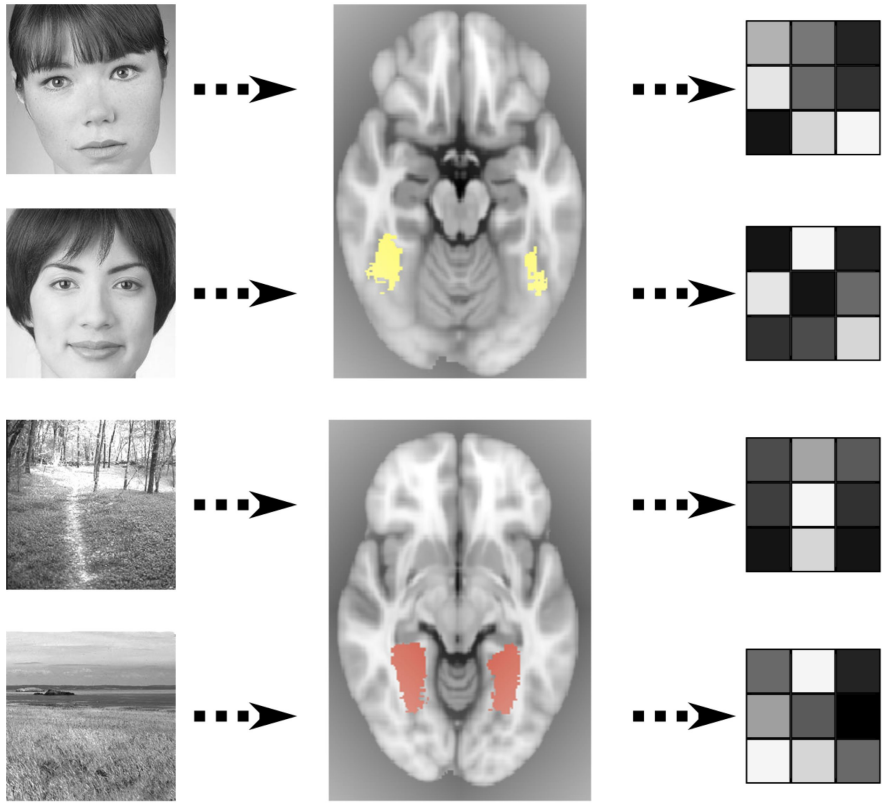

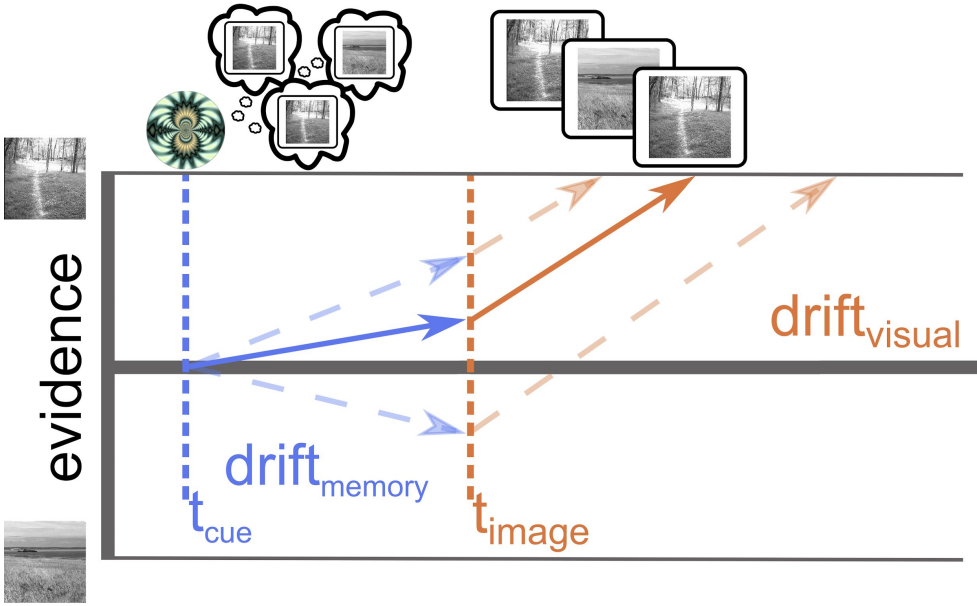

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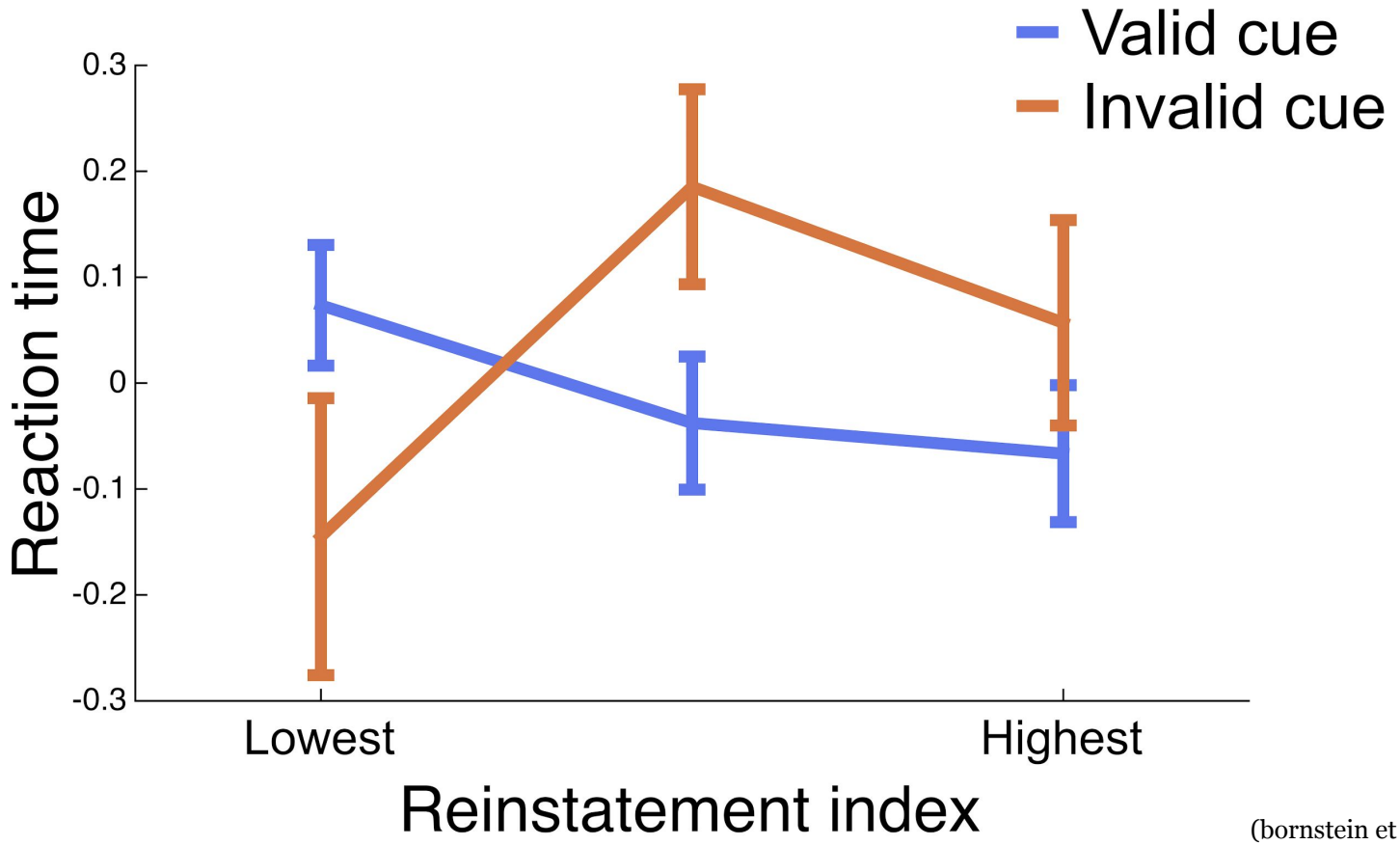
memory sampling reduces uncertainty



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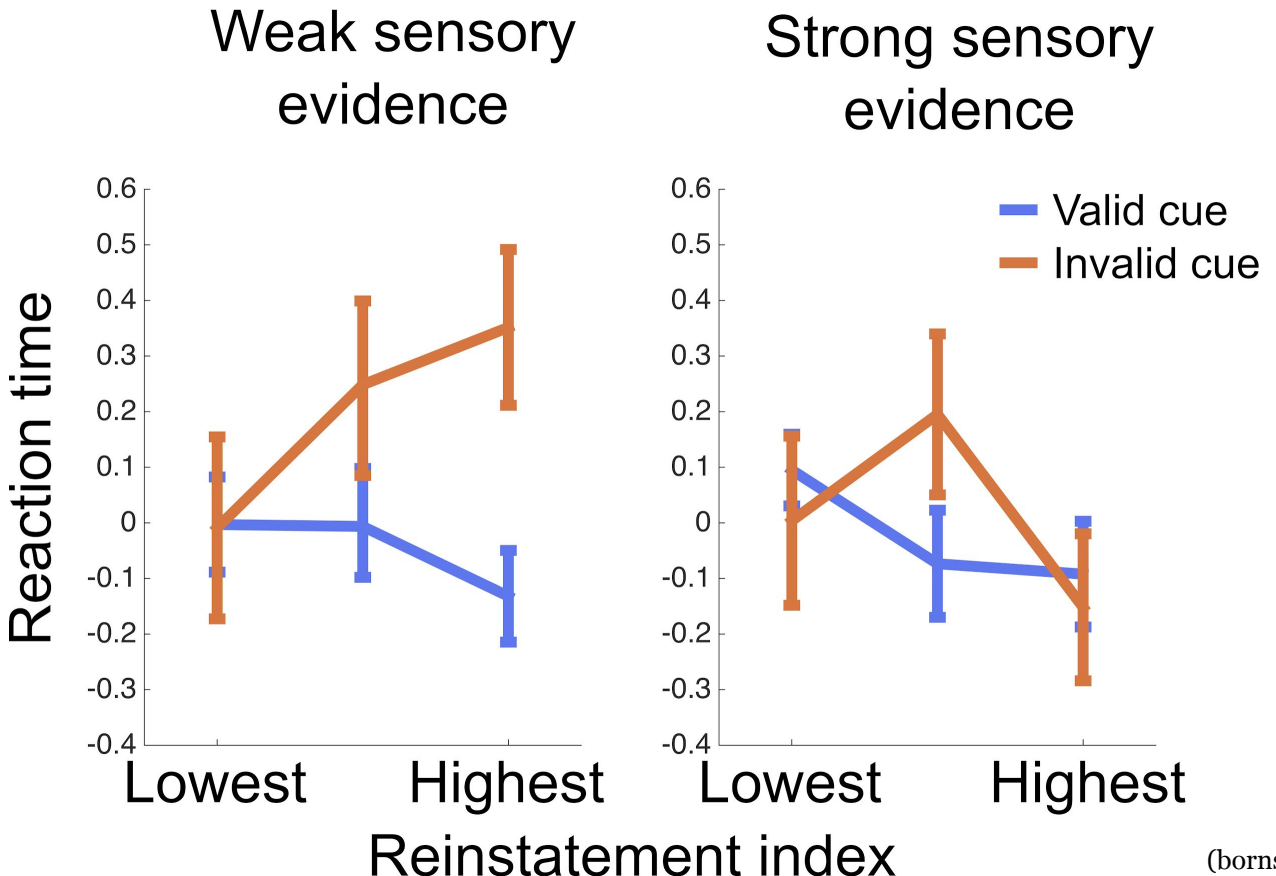
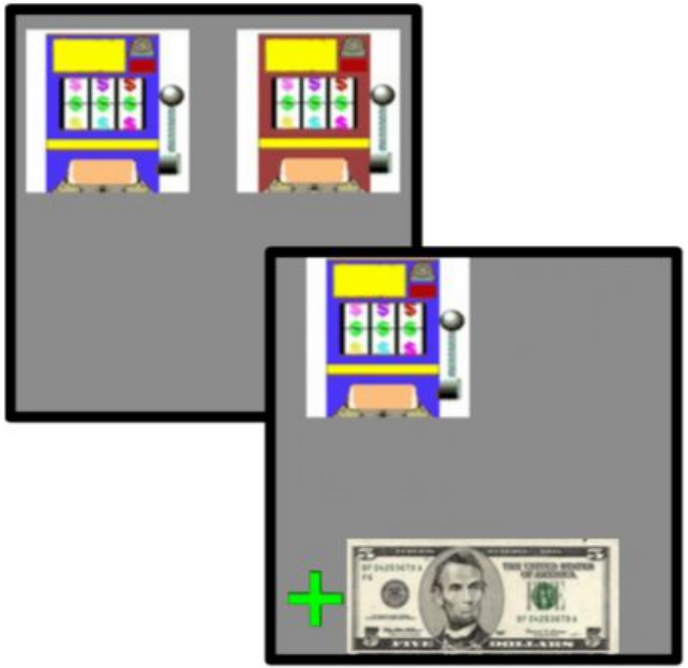


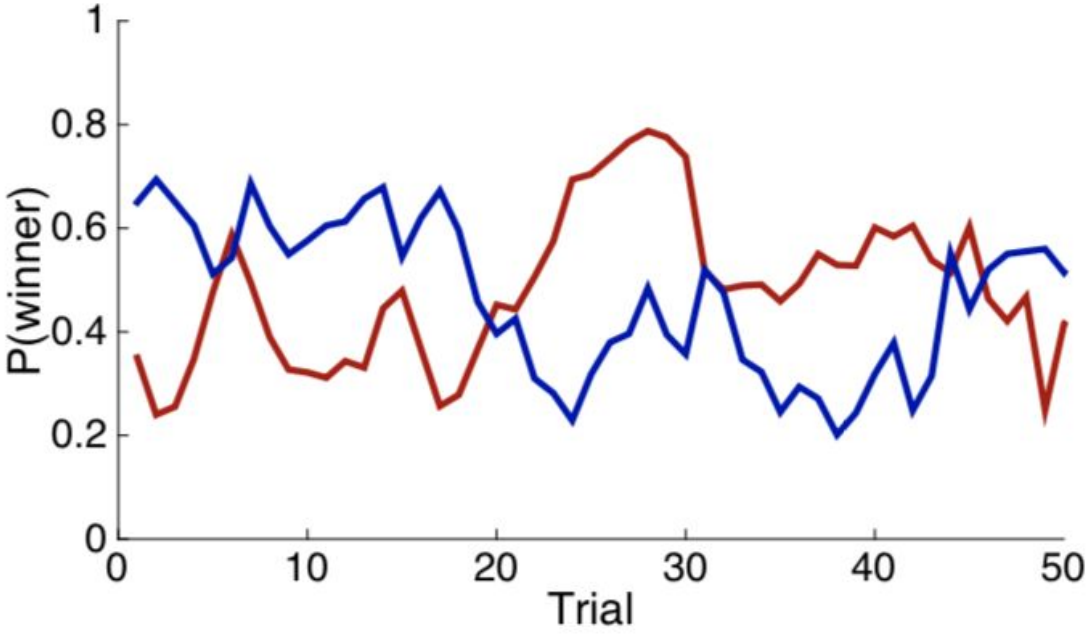
(bornstein et al *under review*)

interim summary

- memory samples can reduce uncertainty about state
- pre-emptive memory-guided uncertainty reduction can reduce the need for sensory-guided uncertainty reduction
- multiple streams of evidence can be sampled to perform state inference
  - and are weighed by their informativeness

memory sampling in a two-armed bandit task





$0

$$Q_t(a) = Q_{t-1}(a) + \alpha[R_t - Q_{t-1}(a)]$$

$0

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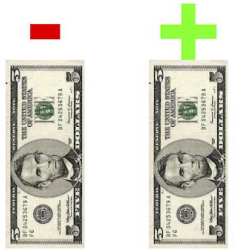
$2.50

$$Q_t(a) = Q_{t-1}(a) + \alpha[R_t - Q_{t-1}(a)]$$

-$1.25



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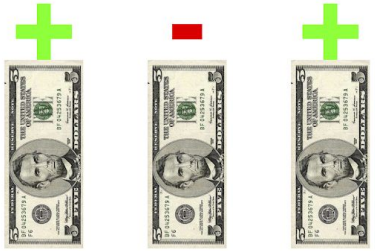

$1.88

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$5

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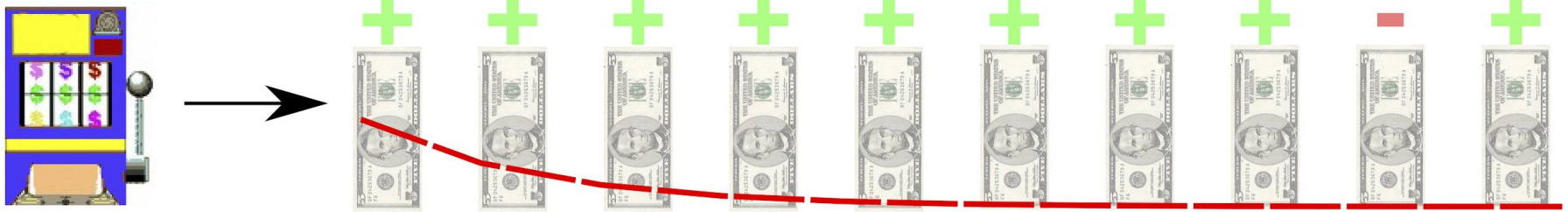

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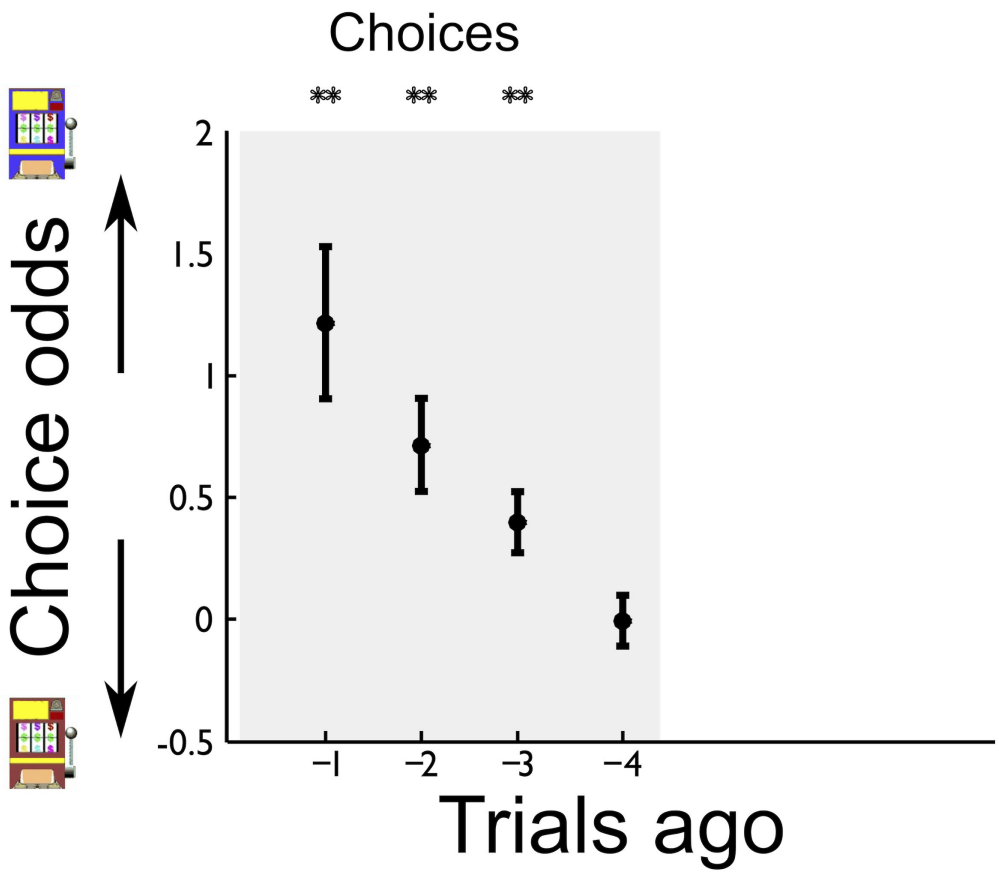

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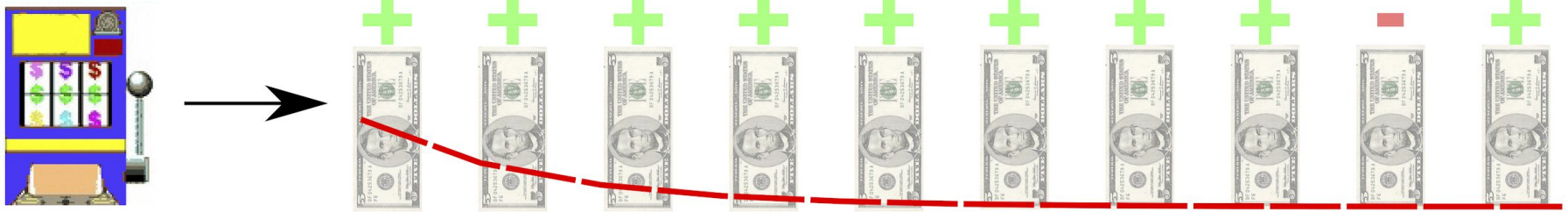

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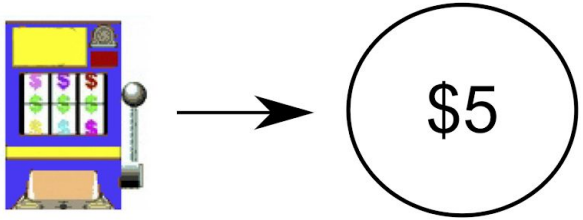

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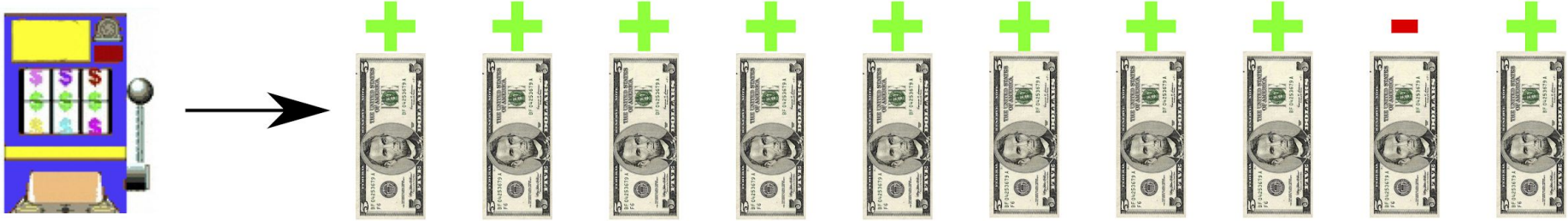
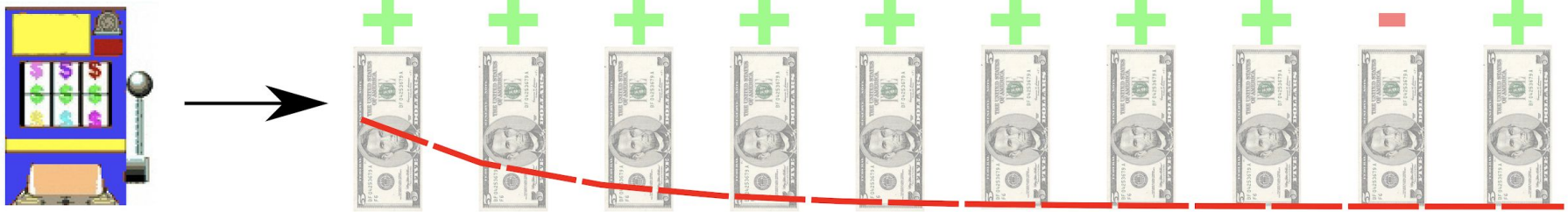
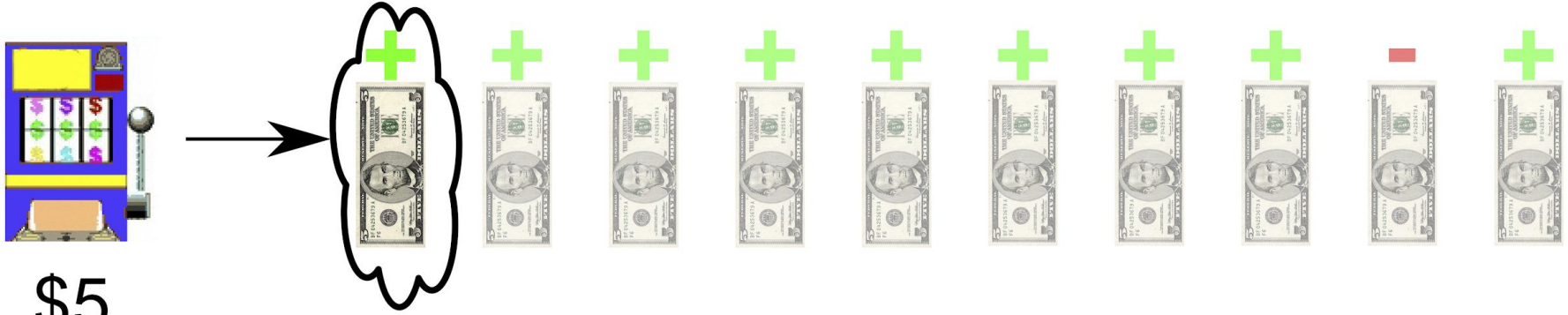




$5

$$P(Q_t(a) = R_i) = \alpha(1-\alpha)^{t-i}$$



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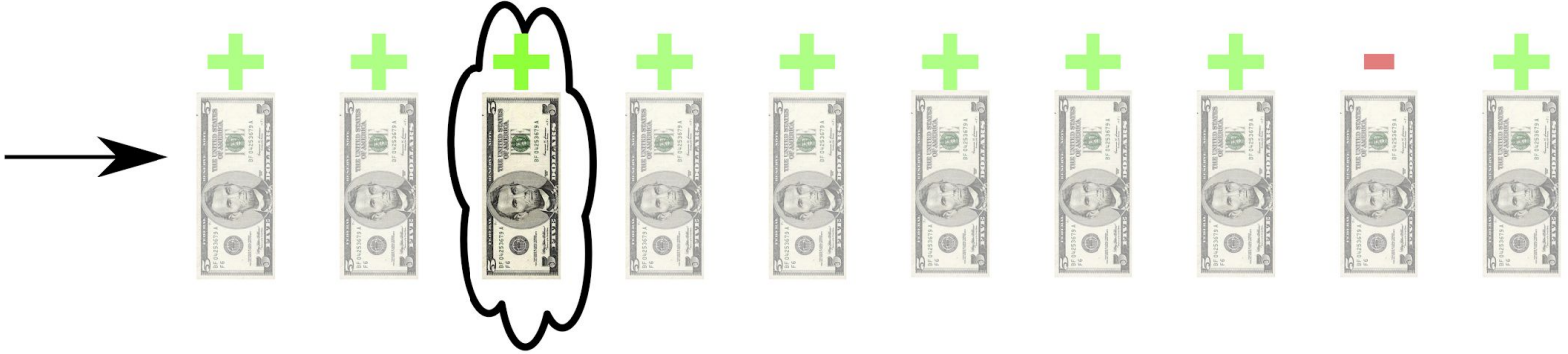

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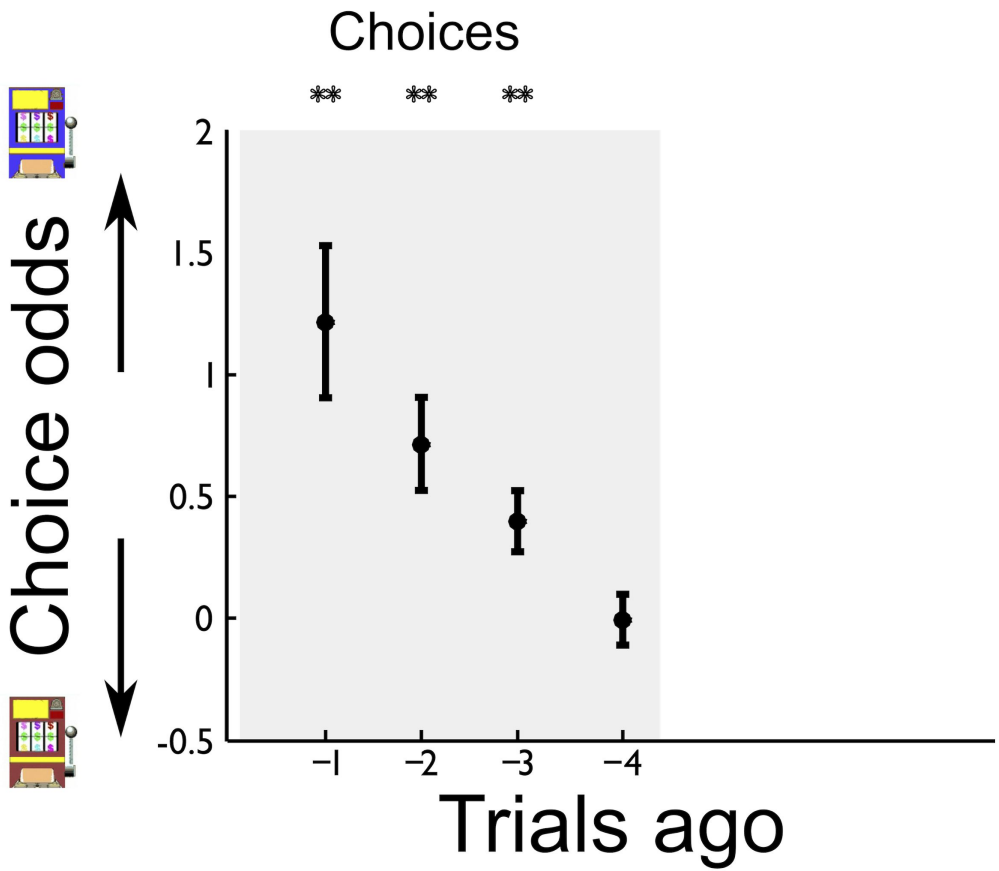

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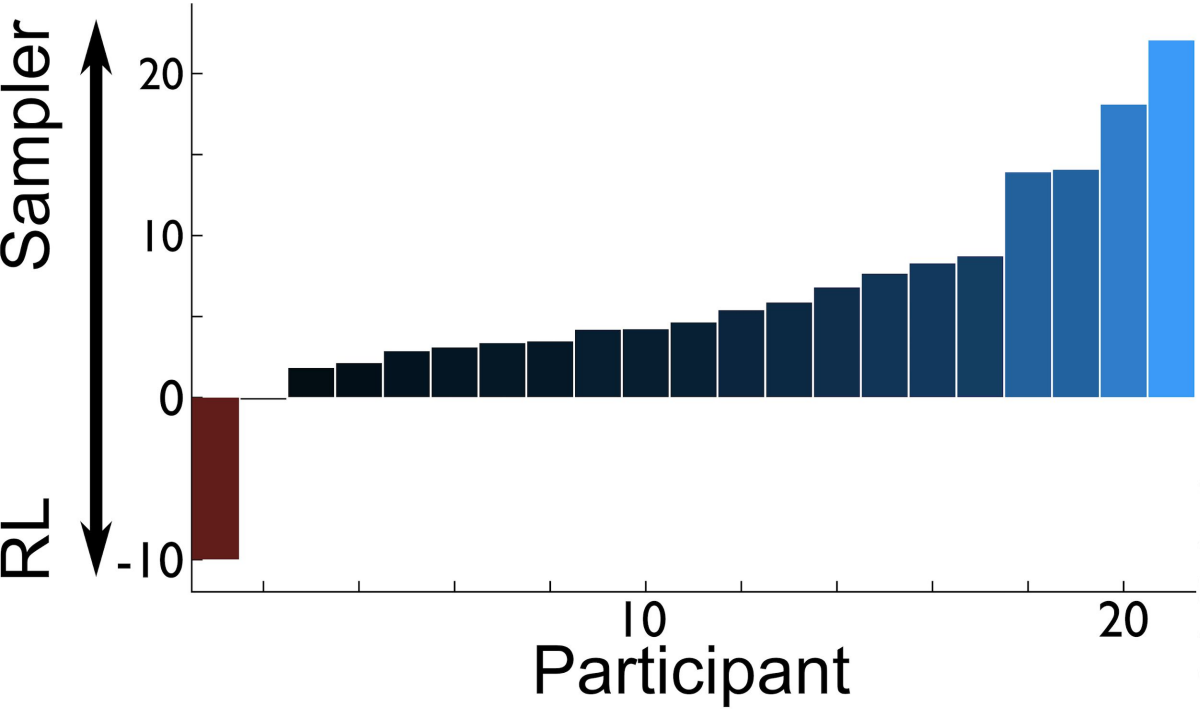
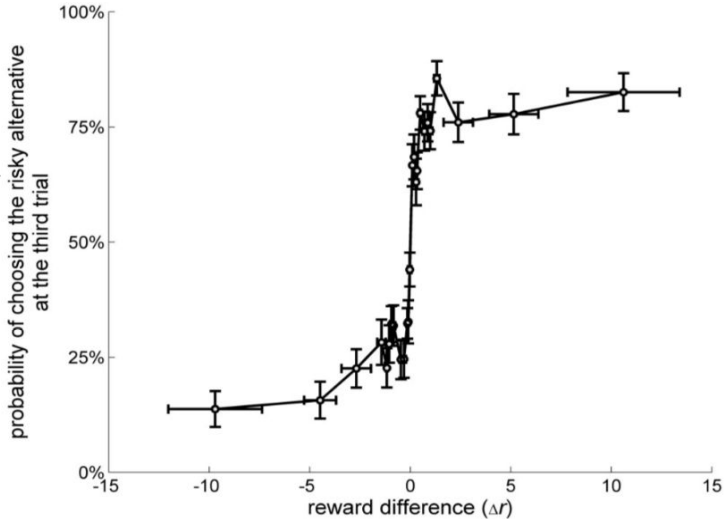
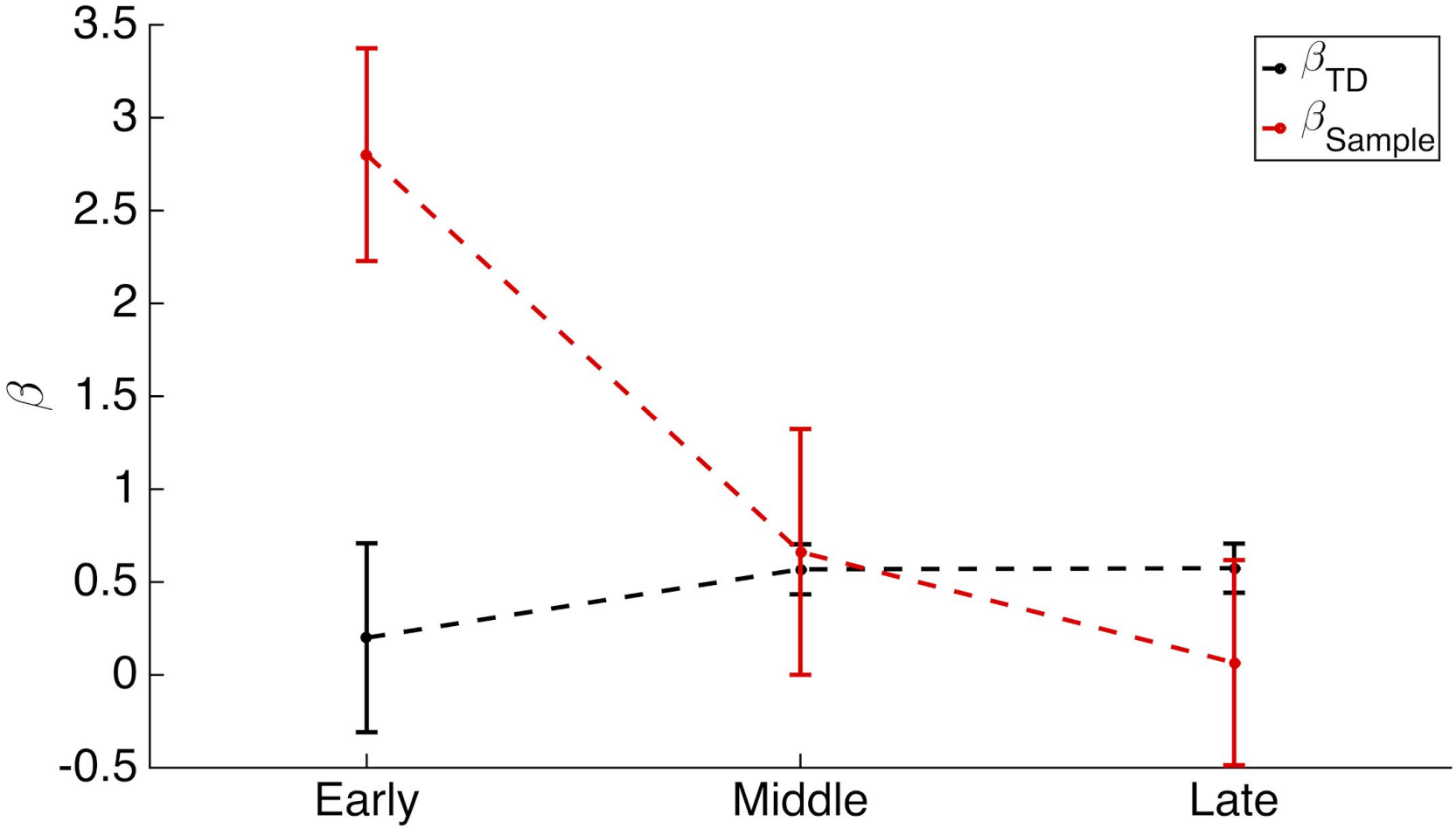


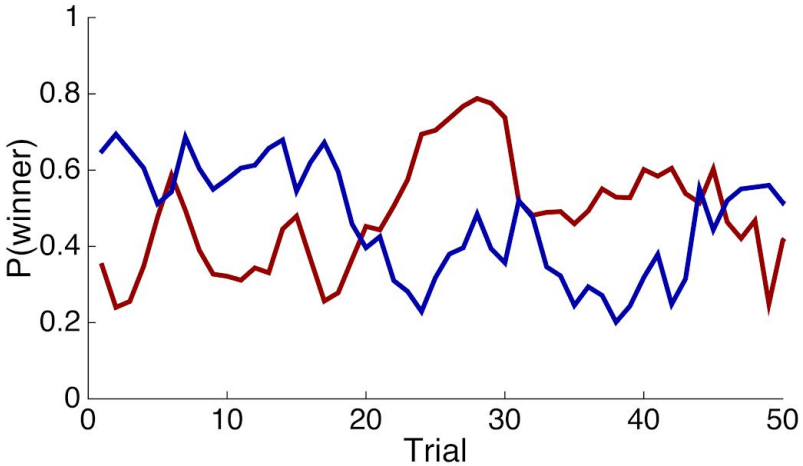


(bornstein et al 2017)



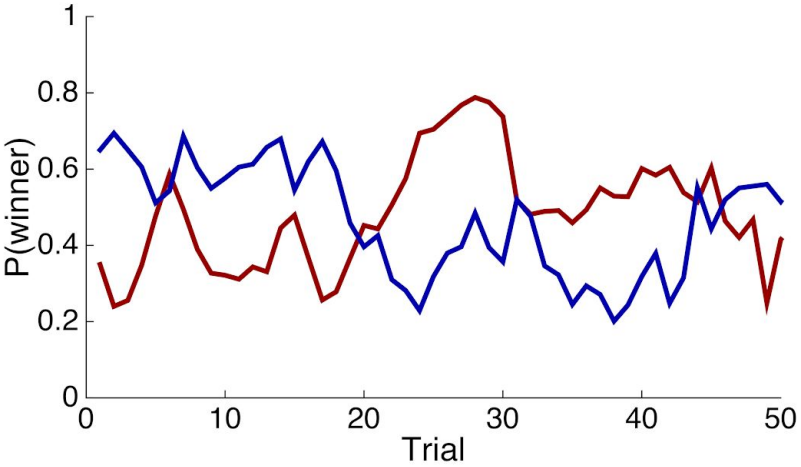
(bornstein et al 2017)

“ticket bandit” task

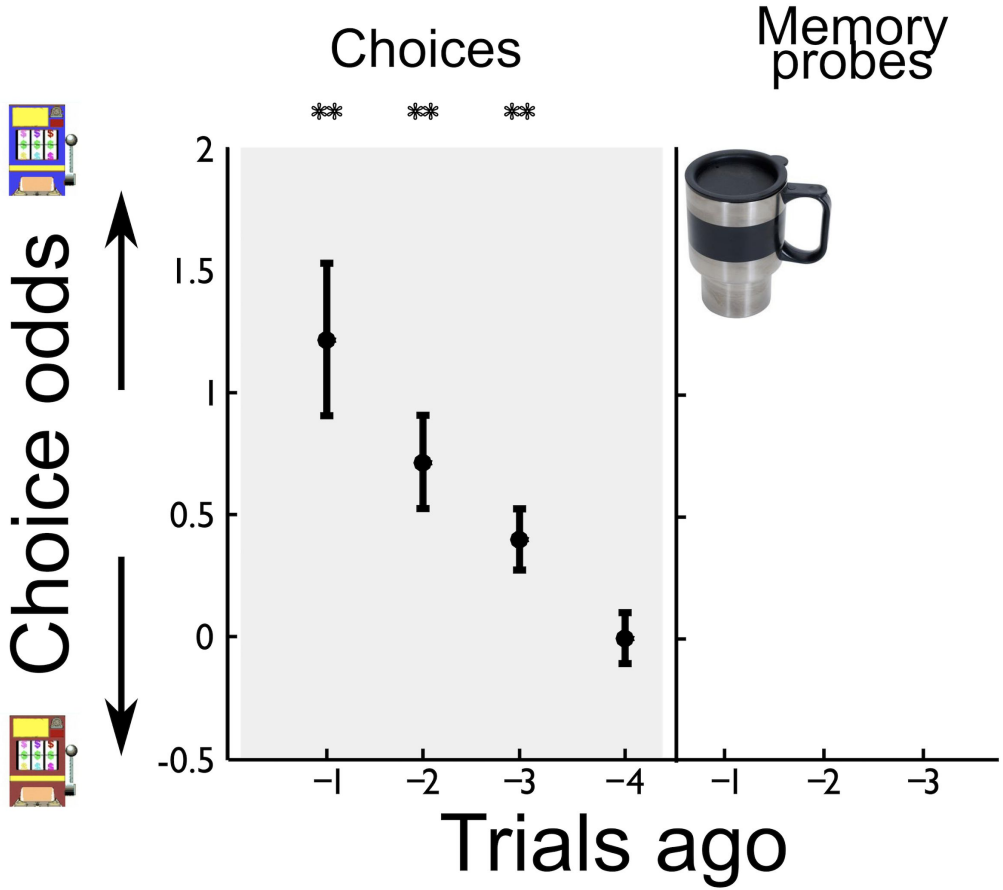


(bornstein et al 2017)

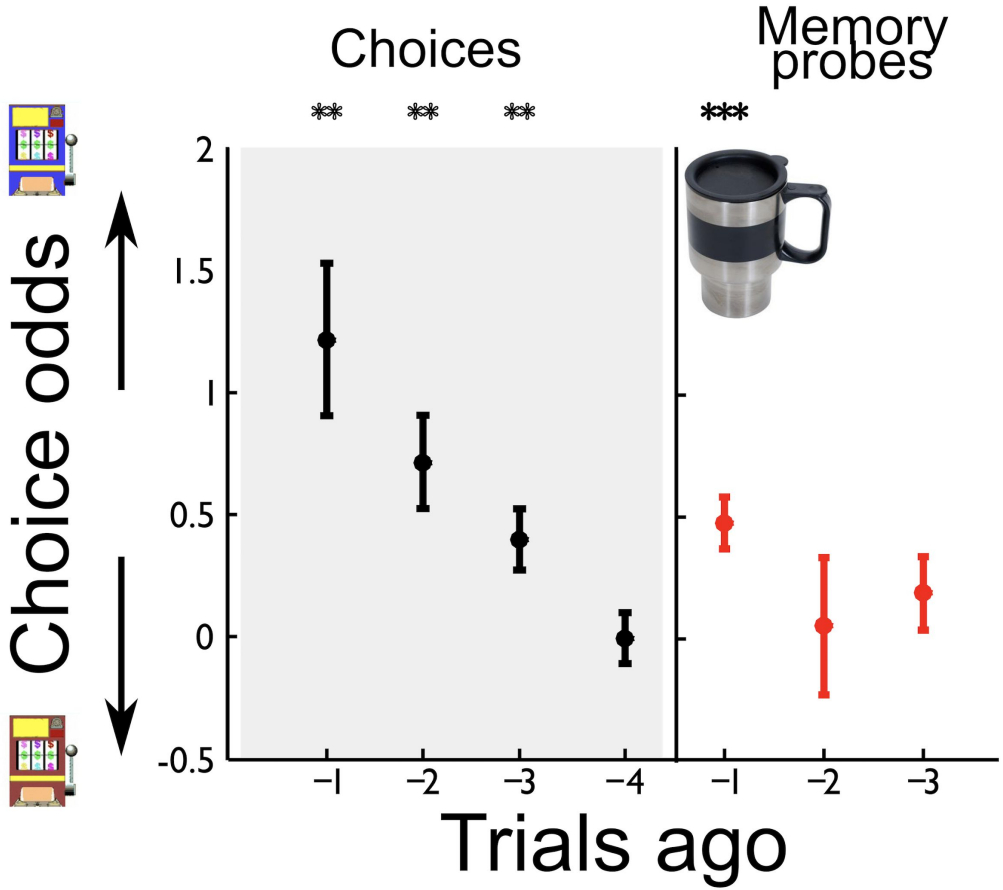
“ticket bandit” task



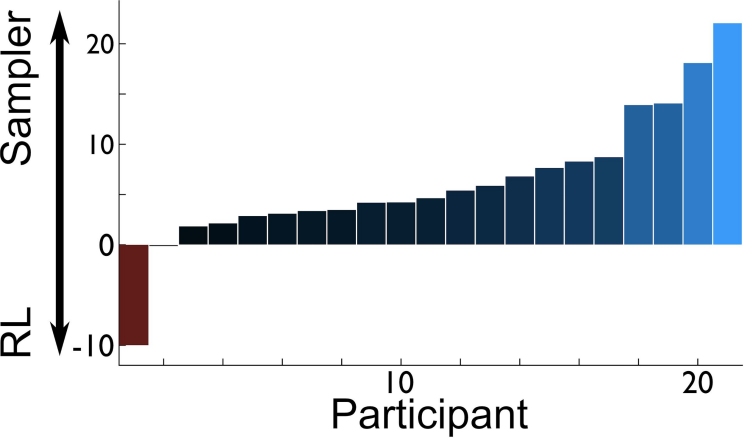
(bornstein et al 2017)

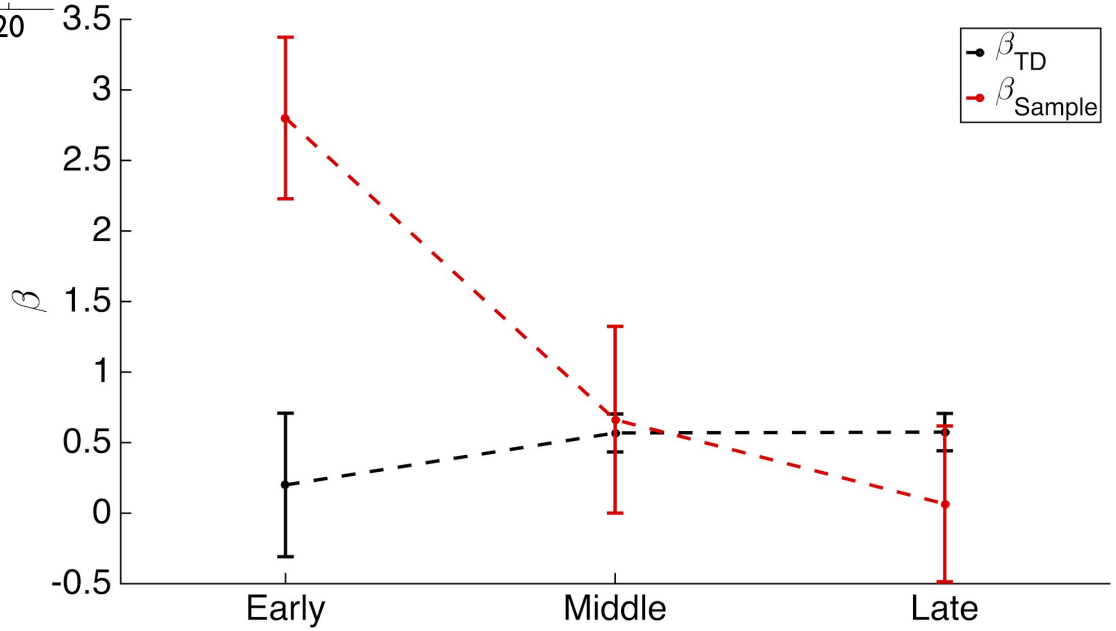


(bornstein et al 2017)



(bornstein et al 2017)





(bornstein et al 2017)

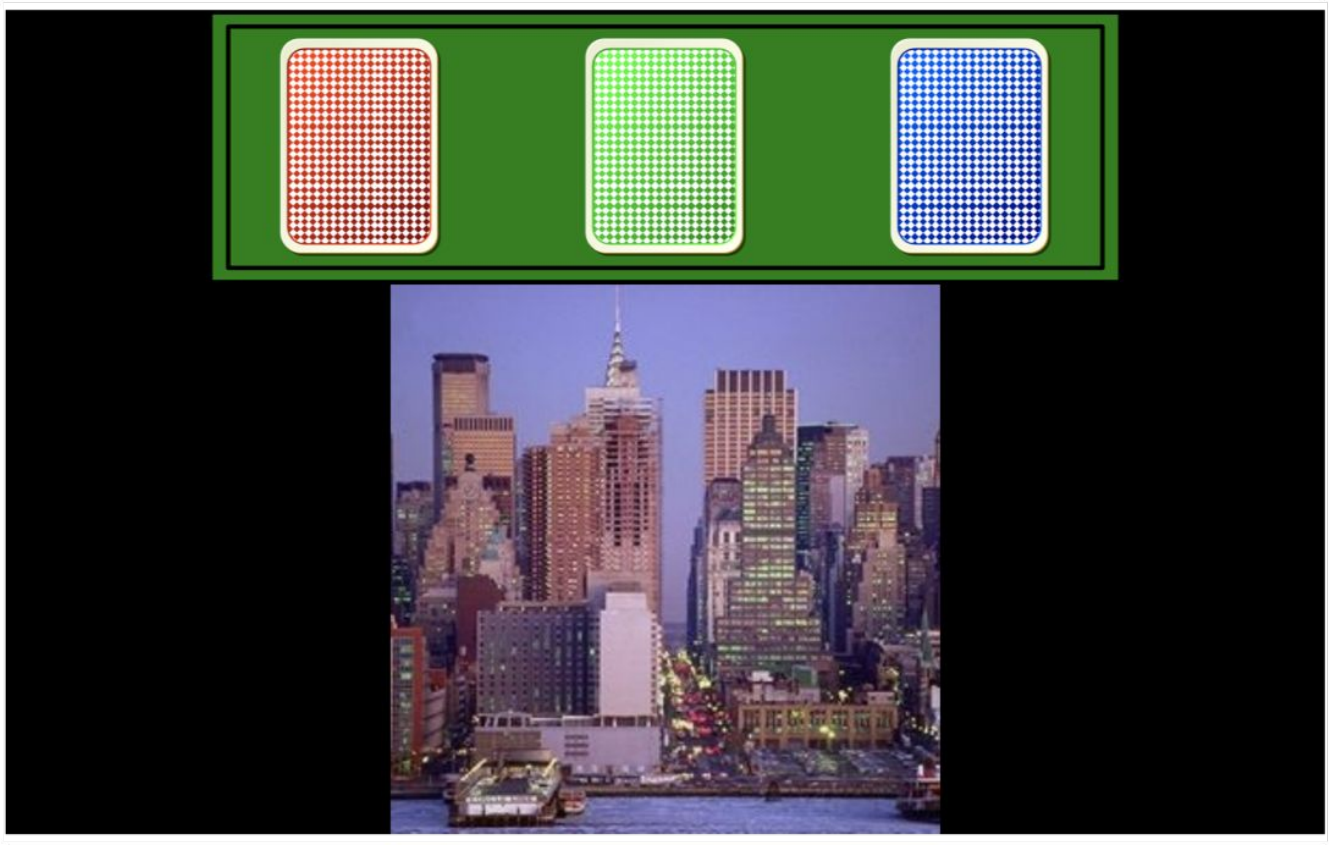
interim summary

- memory sampling can be biased by incidental reminders of individual experiences
- suggests role for *episodic* memory
- less need for memory sampling when task becomes well-learned

next: more to a memory

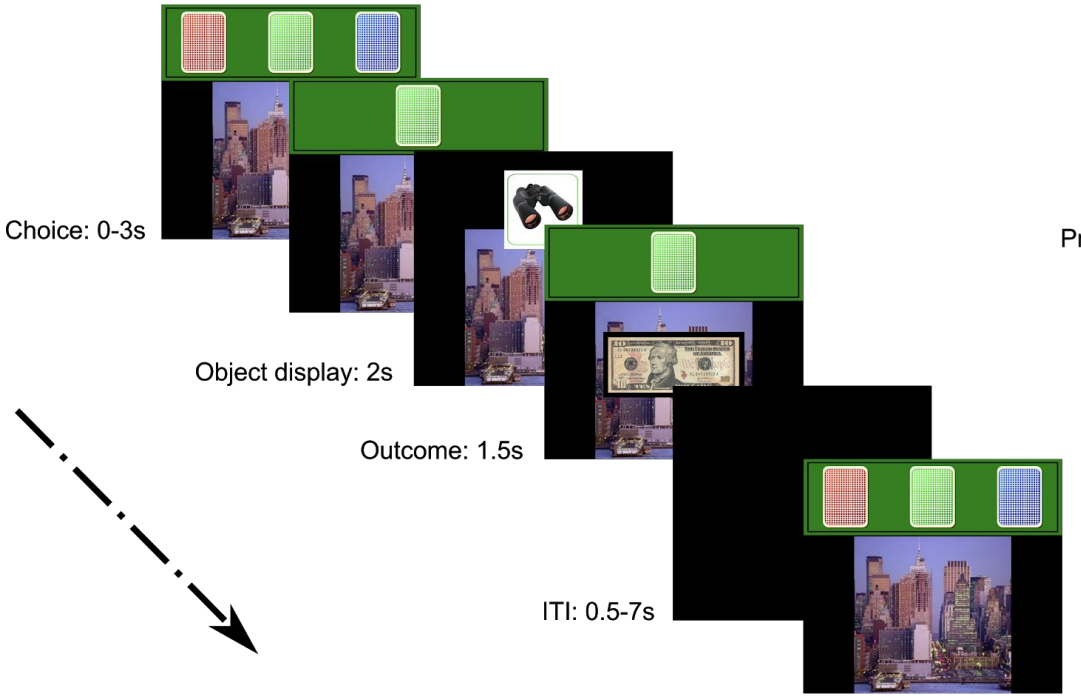
- episodic memories are more than just actions and values
- also carry *context*: associations with other, nearby, experiences (howard & kahana 2002)
- does this other episodic information *also* affect decisions?

“context bandits” task

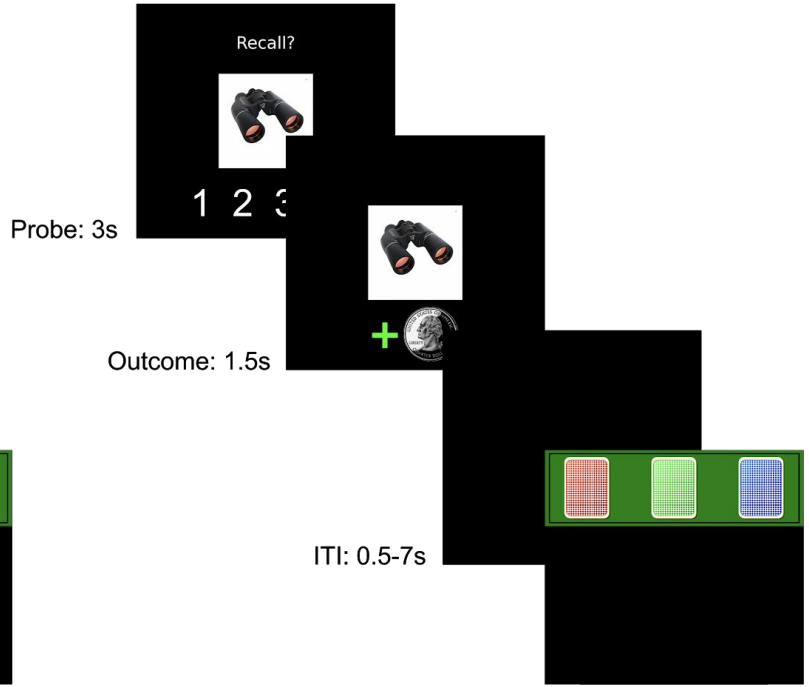


(bornstein & norman 2017)

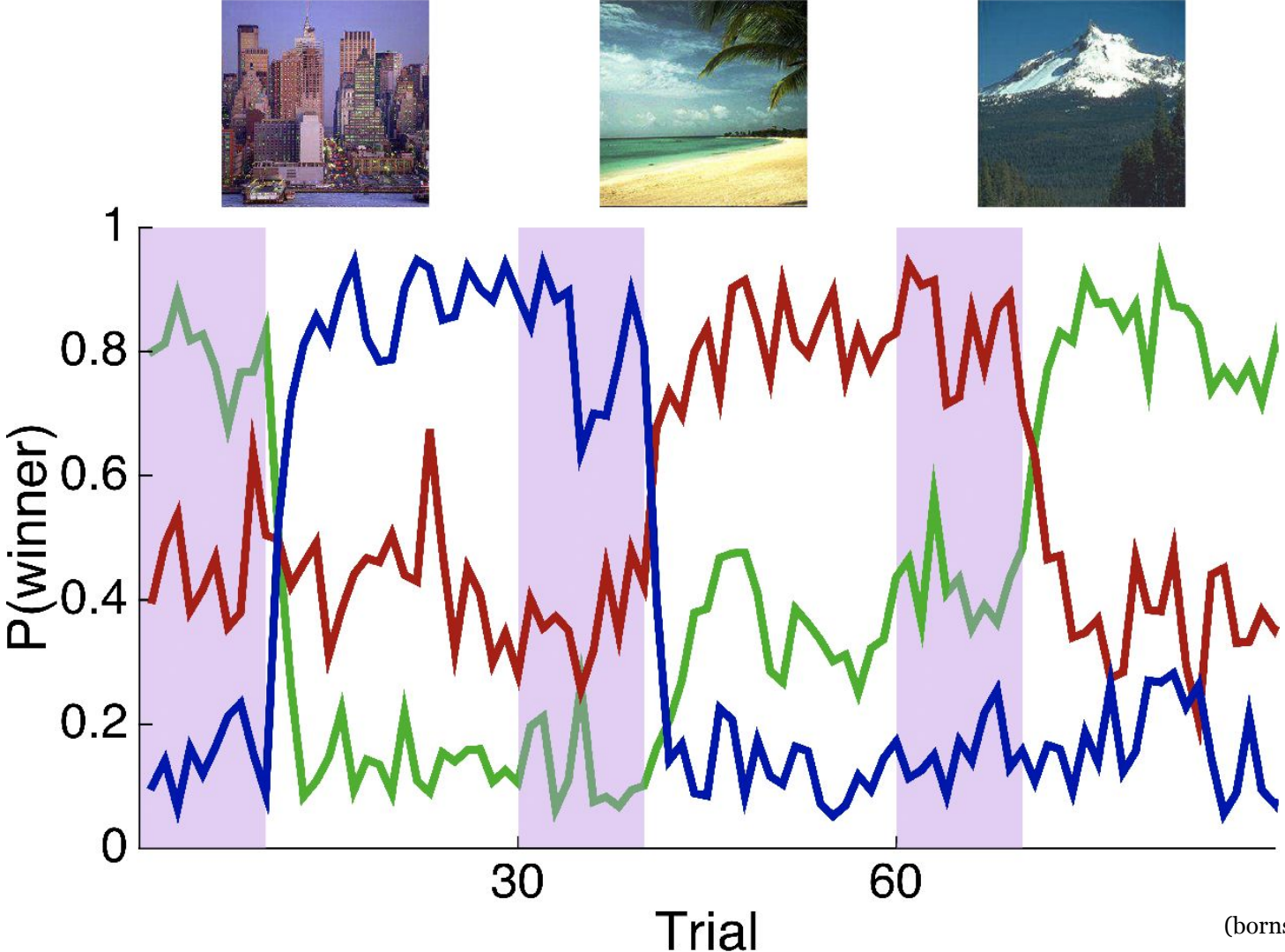
Context room choices



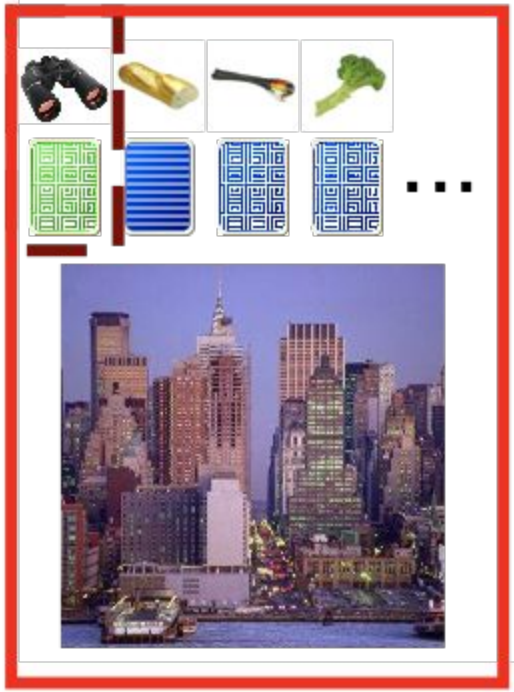
Memory probes



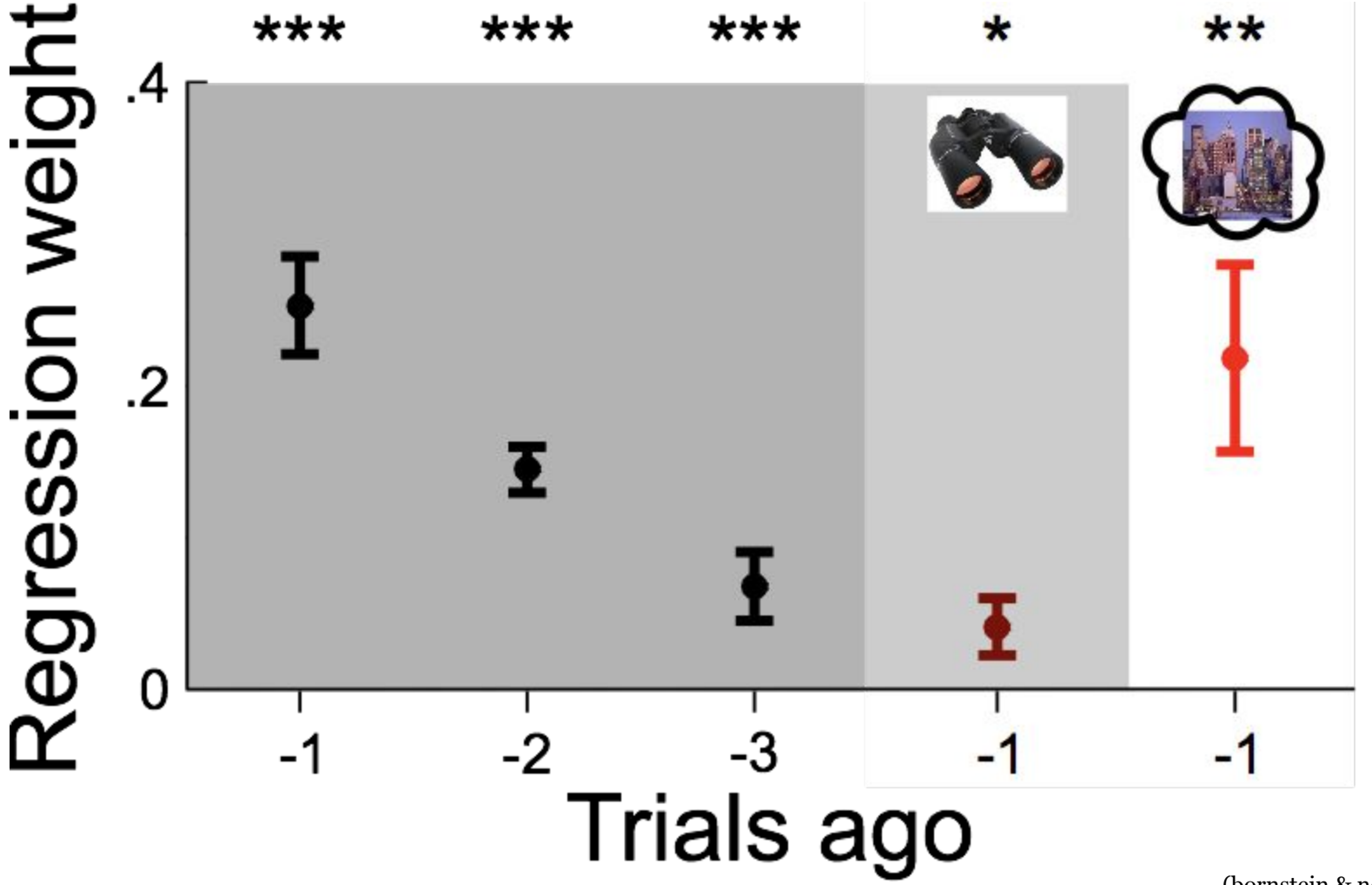
(bornstein & norman 2017)



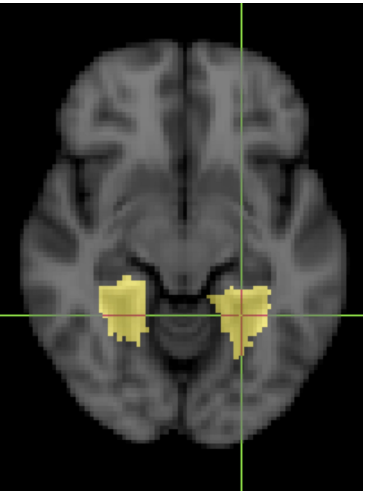
(bornstein & norman 2017)

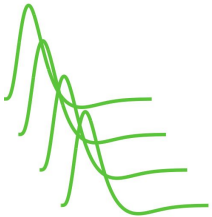


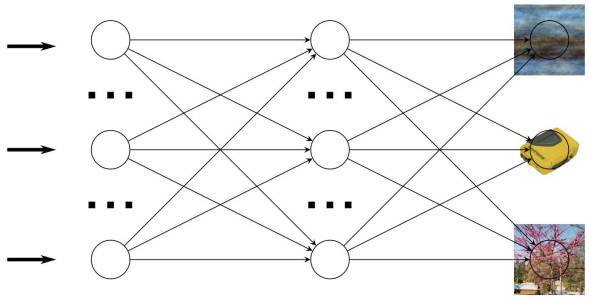
(bornstein & norman 2017)



(bornstein & norman 2017)



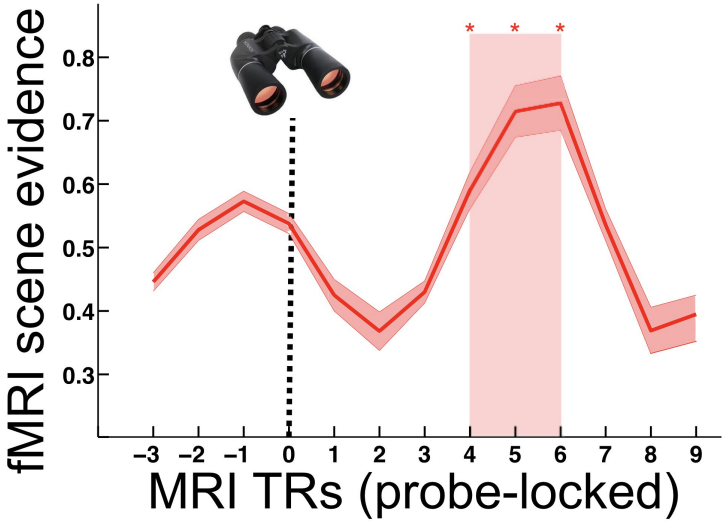




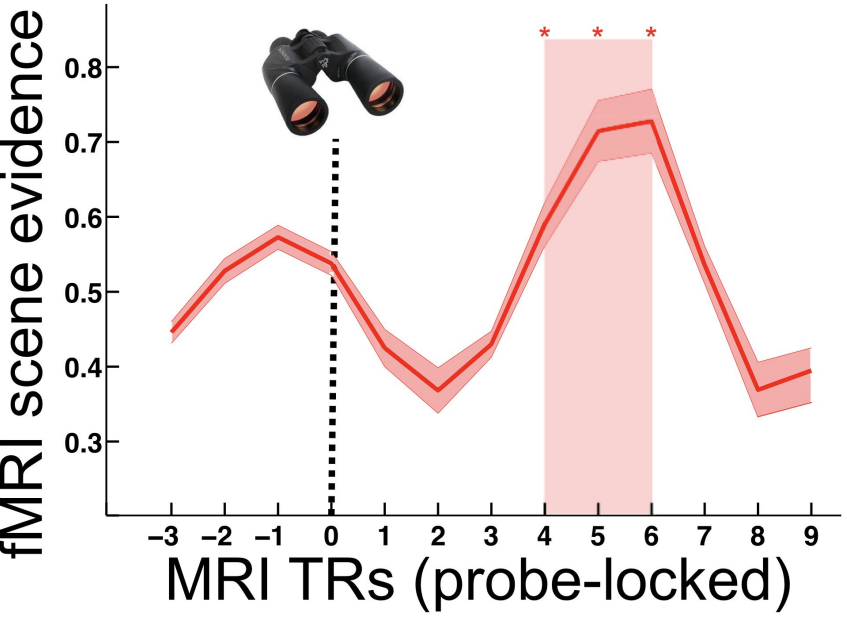
0.13

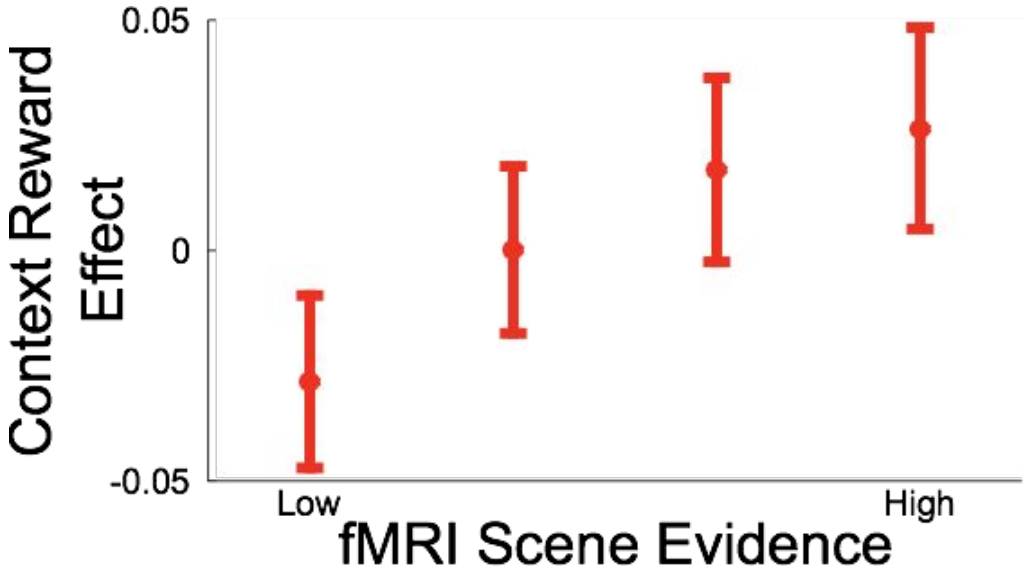
0.05

0.82

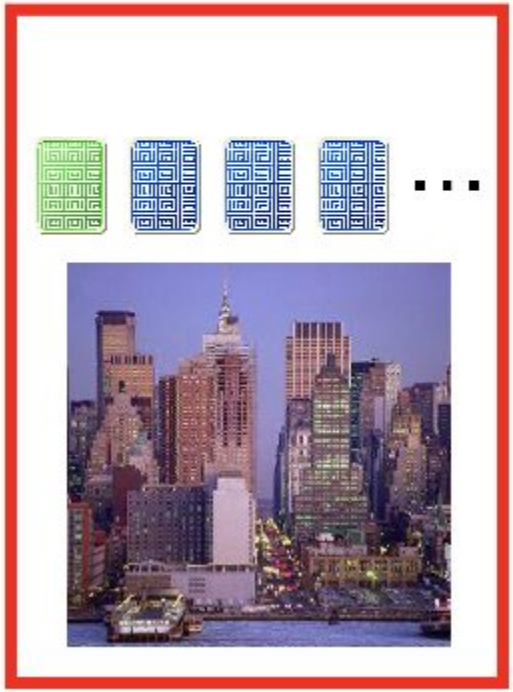


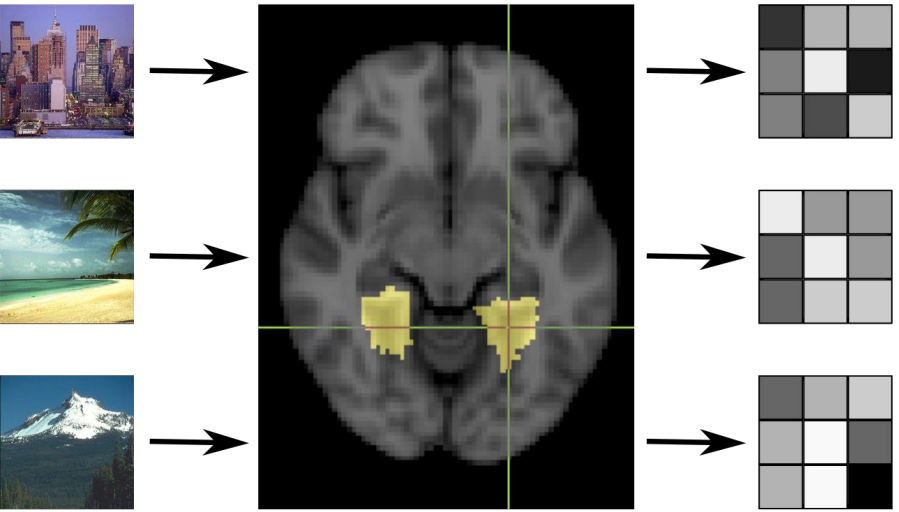
(bornstein & norman 2017)

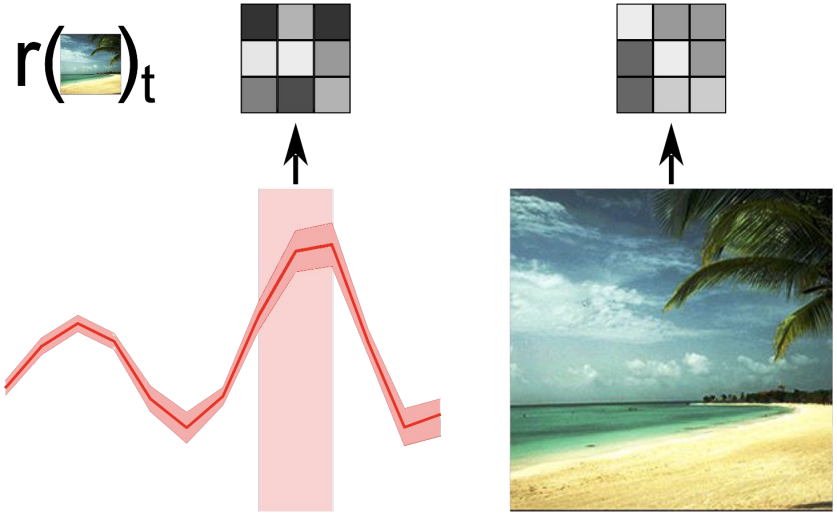


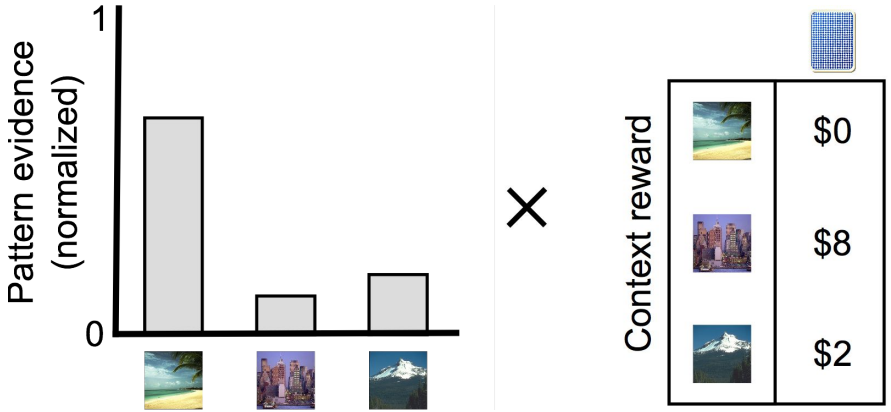


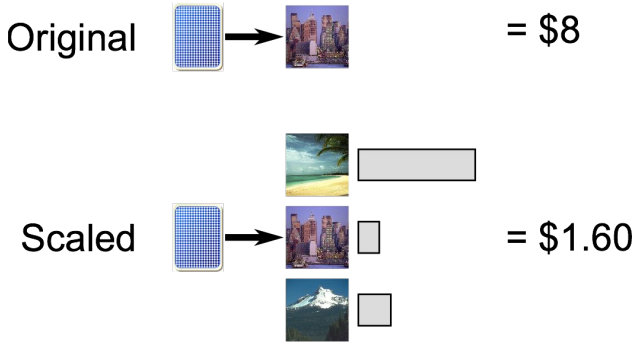
(bornstein & norman 2017)



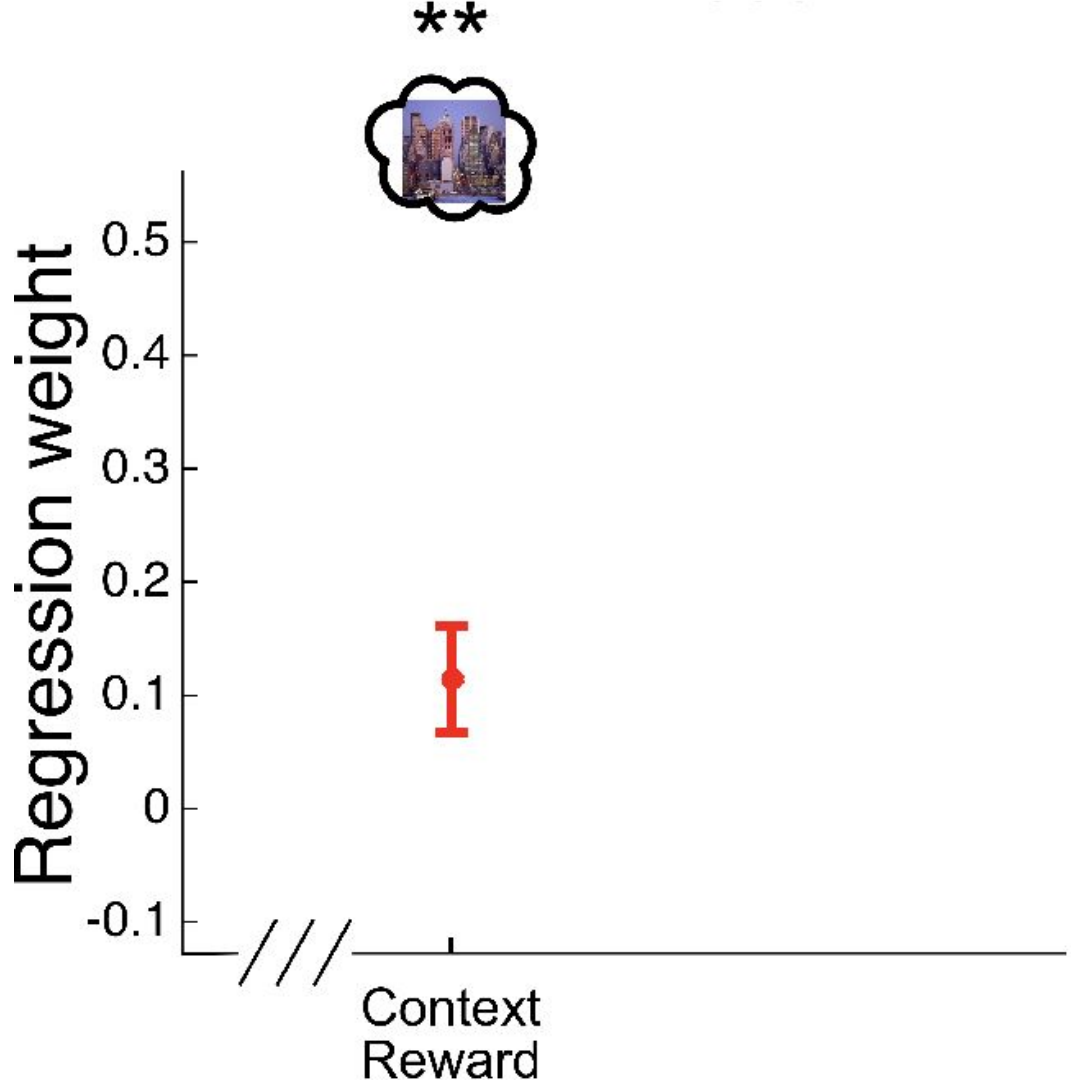




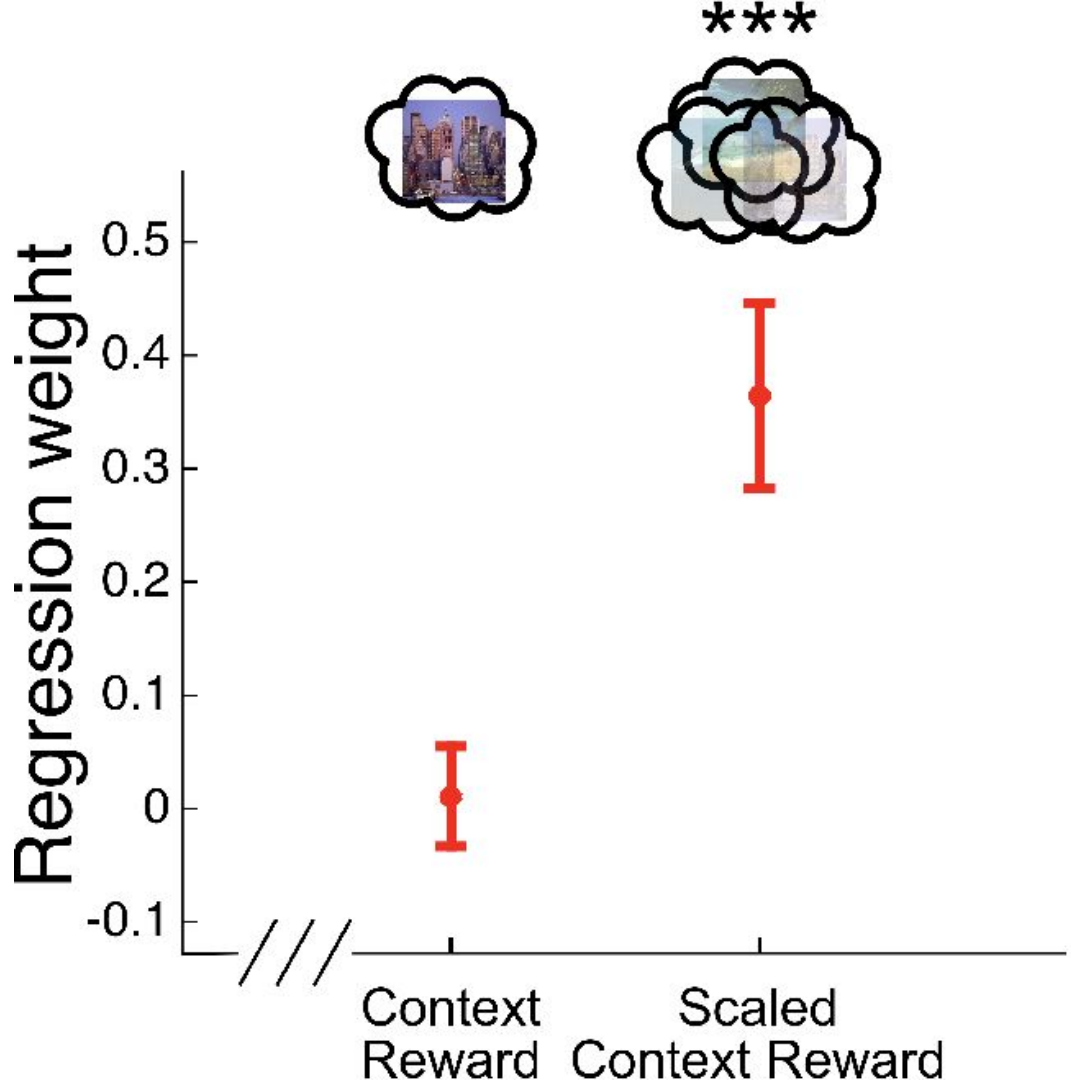




(bornstein & norman 2017)



(bornstein & norman 2017)



(bornstein & norman 2017)

more to a memory

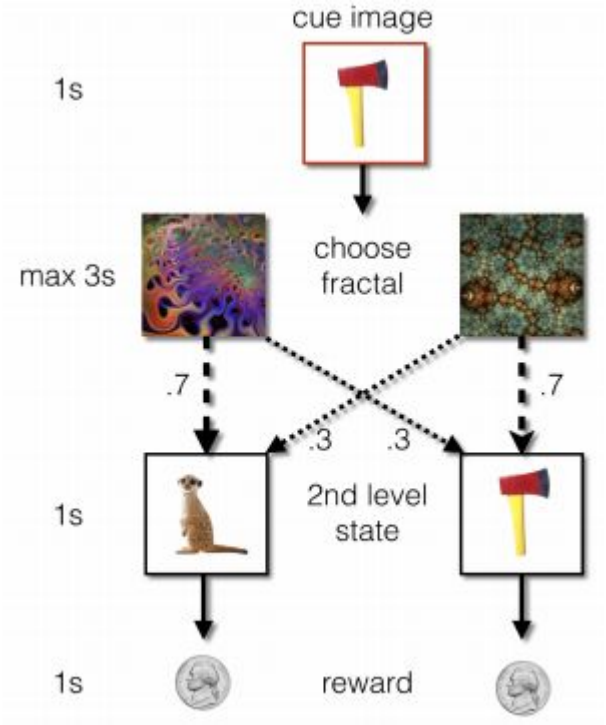
- episodic memories are more than just actions and values
- also carry *context*: associations with other, nearby, experiences (howard & kahana 2002)
- the actions and values in these other experiences can, when they are remembered, also bias decisions
- memory is also not veridical
  - mistaken memories also bias decisions
- what matter is what is remembered *at the time of decision*

last: episodic model-free, or episodic model-based?

is episodic memory sampling “model-free” — guiding towards a specific past action-value pair

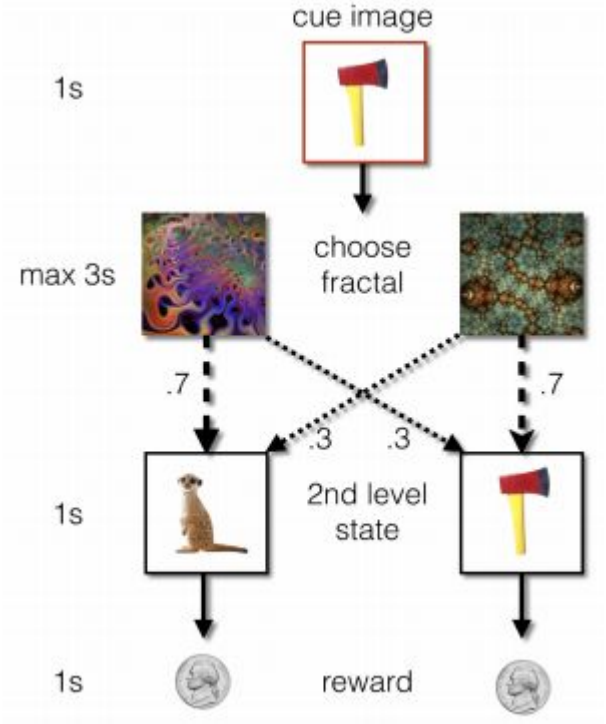
or is it “model-based” — flexibly combined with current transition structure

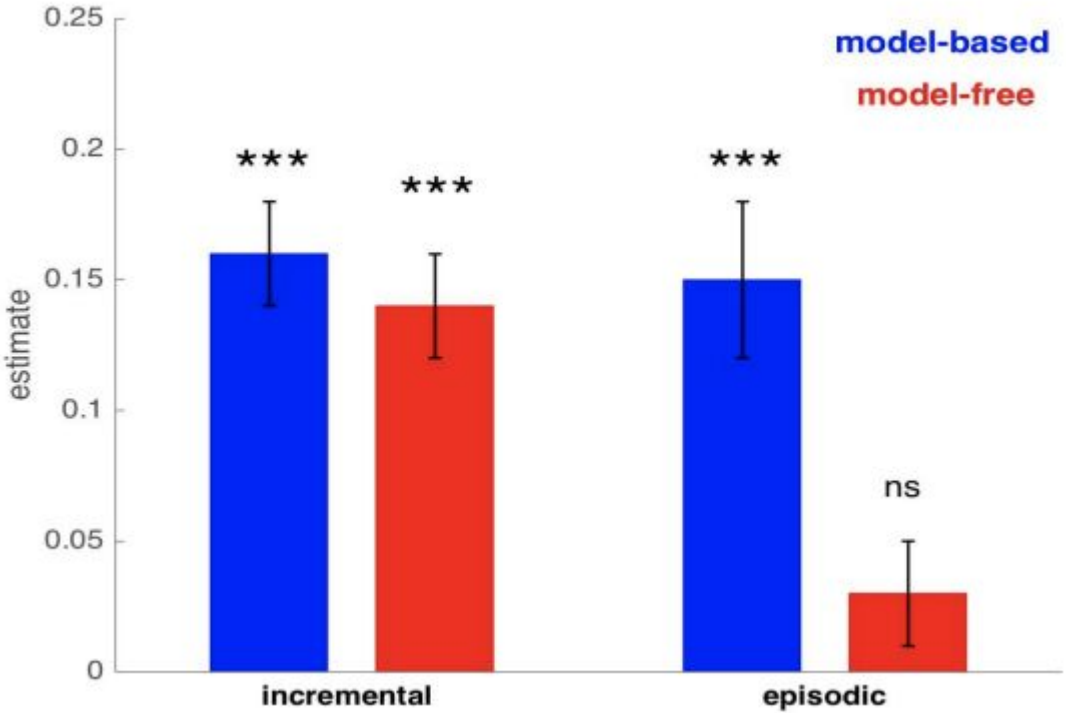
episodic two-step task



(vikbladh et al 2017)

episodic two-step task





see ritter, wang et al 2018 for artificial RNN “discovering” e-mb, but not e-mf

(vikbladh et al 2017)

outline

I. computational role(s) of memories

II. experimental evidence

III. if time: open questions

open q: underlying representations

- neuroscience: a continuum of representations
  - full *semantic* or *grammar* (daw et al 2005; glascher et al 2010)
  - flexible action sequences (doya et al 2002; bornstein & daw 2012)
  - flexible S-S sequences ("successor representation"; dayan 1993; bornstein & daw 2012, 2013)
  - episodes (lengyel & dayan 2008; bornstein & daw 2013; bornstein et al 2017, 2018; vikbladh et al 2018a,b; ritter et al 2018)
- computational RL: many varieties of "model"
  - *sample* models v *distribution* models

open question: distributional or sample representation?
- is a given behavior guided by a distributional or a sample-based representation?
- this can be difficult to distinguish experimentally, at the level of aggregate behavior, because the predictions are, quantitatively, very similar
- this can even be difficult to distinguish in neural representation. (ma et al 2006; fiszer et al 2010)

  - further frontiers: not just states or plans (e.g. categories — http://www.j-paine.org/dobbs/why_be_interested_in_categories.html)
- but: general principles apply across representations — learning incrementally, by experience, direct or simulated

further reading

- all cited papers are at: http://aaron.bornstein.org/ccnss/
  - plus some others i think are worth reading

- next edition of sutton & barto book: http://incompleteideas.net/book/the-book-2nd.html

- forthcoming book: “goal-directed decision making: computations and neural circuits” — ask me for pdfs in a couple months
  - table of contents: http://aaron.bornstein.org/gdcnc/

- happy to talk about research any time ⟹ aaron@bornstein.org

open q: trajectory sampling?

- no one has yet decoded *multi*-step decisions, either offline or online

- thus it's an open question whether planning is trajectory sampling, or single-step value-function updates

open q: how do we arbitrate?

- uncertainty-based arbitration thought to require an arbiter
- little evidence for one
- “bottom-up” arbitration? (eisenreich et al 2017; bornstein & cohen in prep)