

Rational use of long-term & working memory: A normative account of prospective memory



PM Emphasis

PM payoff relative to

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Background

We often simultaneously pursue plans at different time scales given noisy perception, varying memory load, & varying payoffs. e.g.

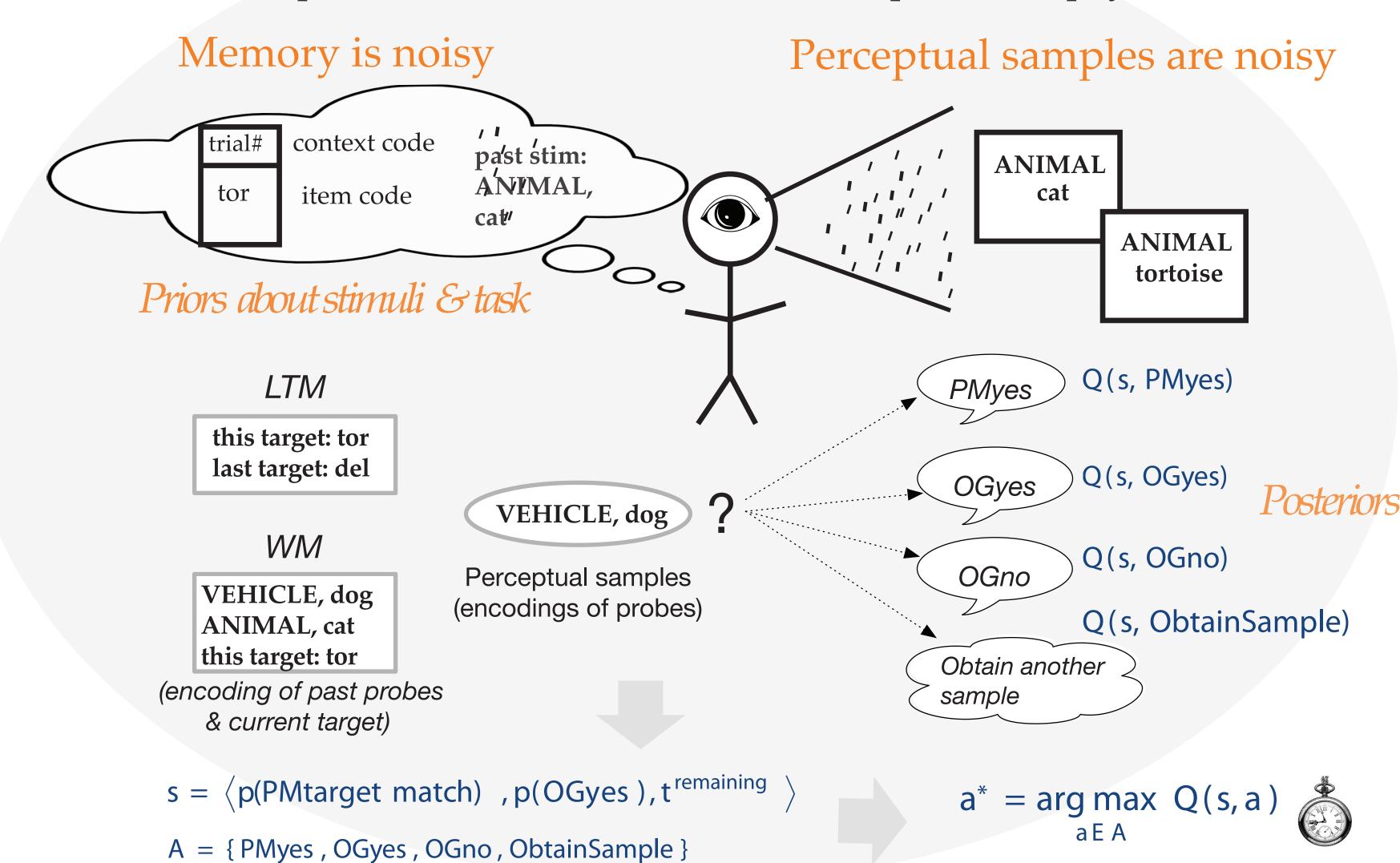
- A task for proximal/immediate time (ongoing or OG task)
- Delayed/prospective task for a future time

This capacity, Prospective memory (PM), requires (a) strategic control of noisy working & long-term memory (WM-LTM; c.f. multi-process model, Einstein et al 2005) & (b) optimal action control strategy.

How does a rational agent use memory & control to solve PM?

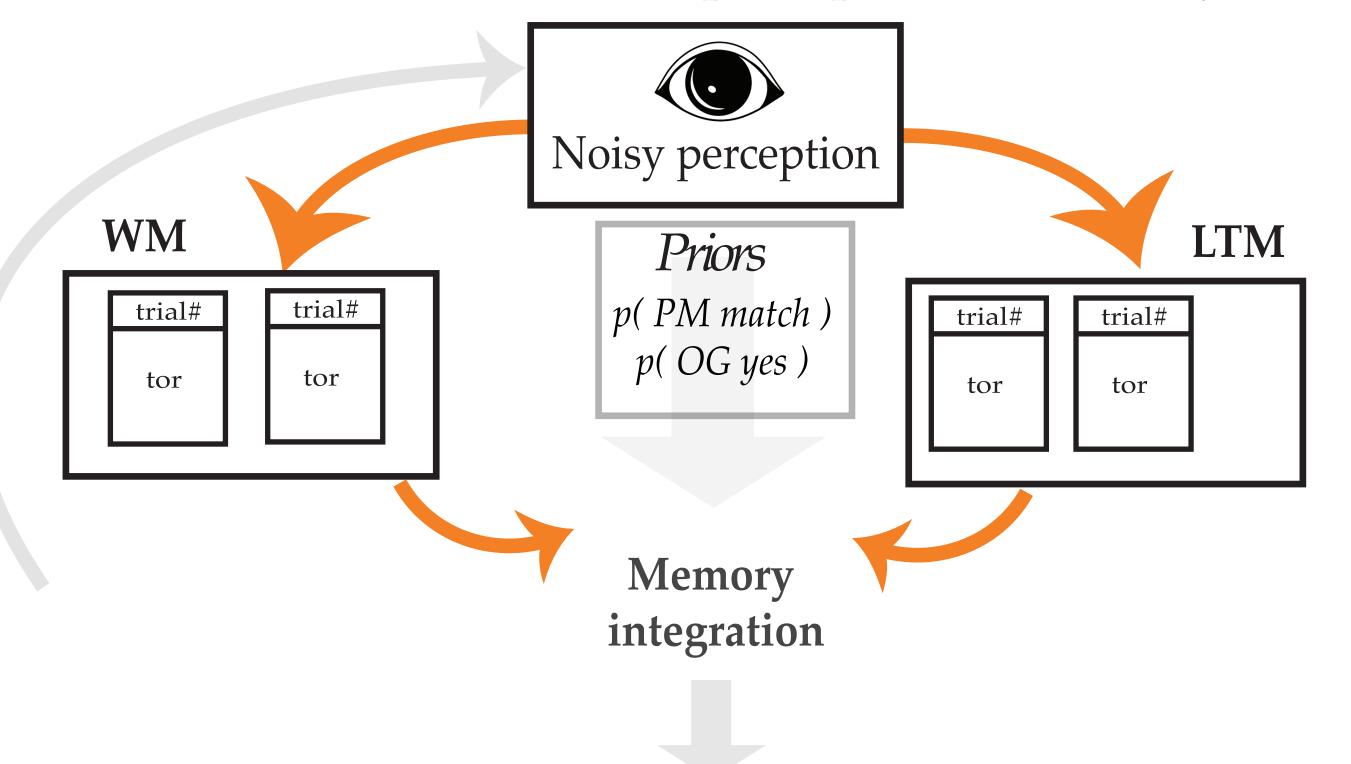
II. Behavioral paradigm Immediate task (OG): Category match Instruction **ANIMAL** Delayed task (PM): Syllable match ('tor') **VEHICLE** \mathbf{PM} Block order: Target: tor **BUILDING** * no-PM (baseline OG) find every **ANIMAL** occurrence * PM tortoise of target item **SUBJECT** Correct responses: YES NO NO PM YES Einstein et al. 2005

Agent must make a response before deadline. Given posterior distributions of correct reponses, & payoffs.

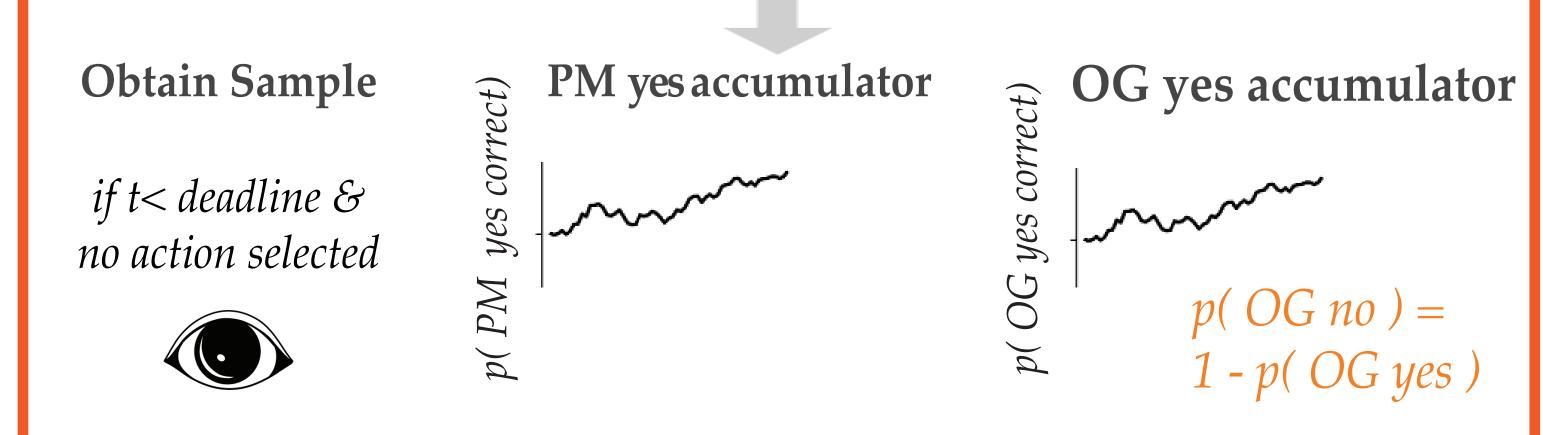


Rational WM-LTM recruitment: A tripartite normative model

WM: noisy encoding of ongoing task (& target) LTM: noisy encoding of current & past PM targets Parallel accumulators with no bounds draw samples to determine a match between perception & memory



s = < p(PM match), p(OG yes), timeLeft >



For each state, A, set of all possible actions is:

A = { Obtain Sample, PM yes, OG yes, OG no }

Q-learning computes optimal policy, which selects action with higer expected value. At each time point optimal policy determines whether to draw another sample & risk going past deadline, or

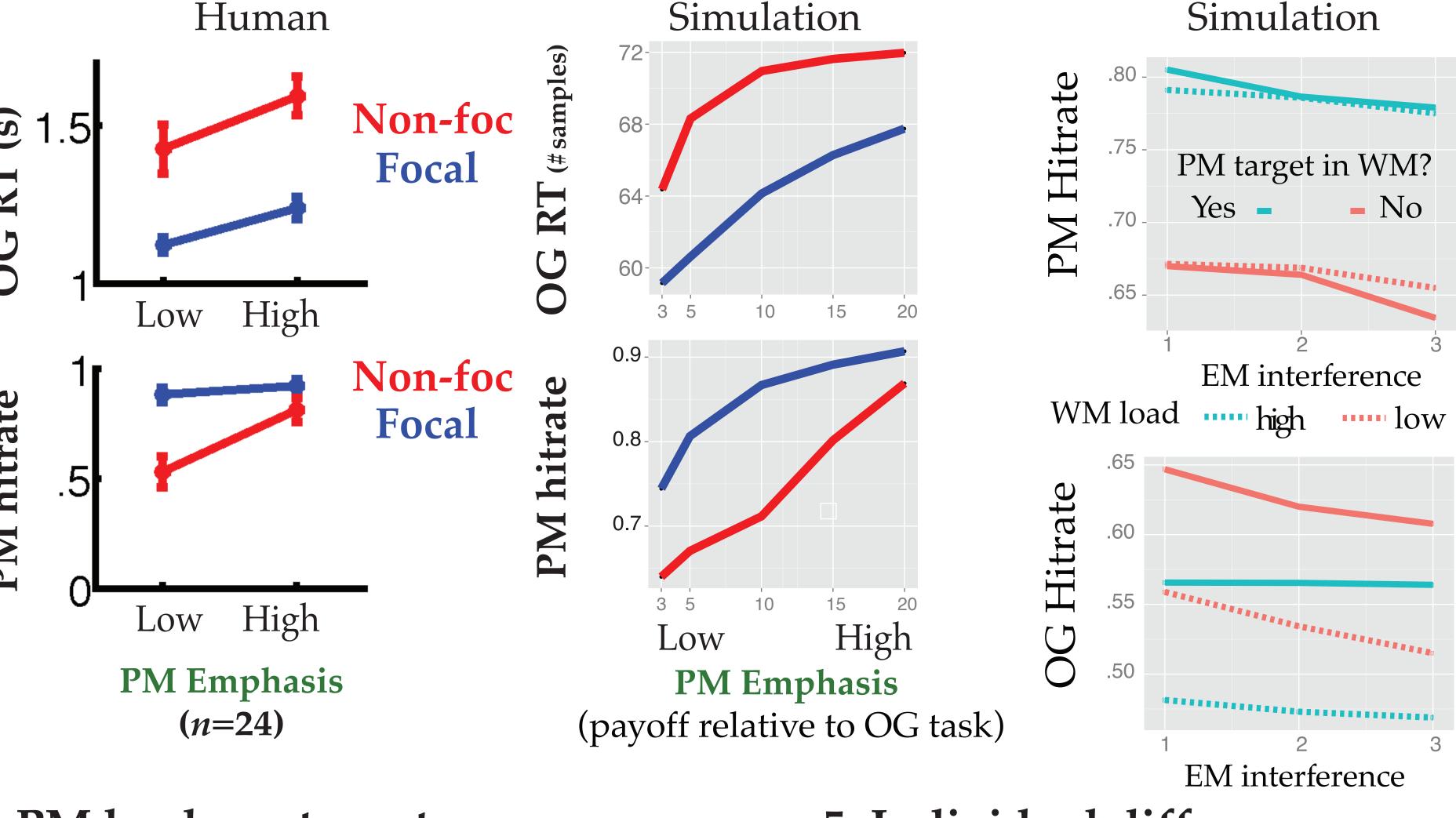
make a response. $a^* = argmax Q(s, a)$

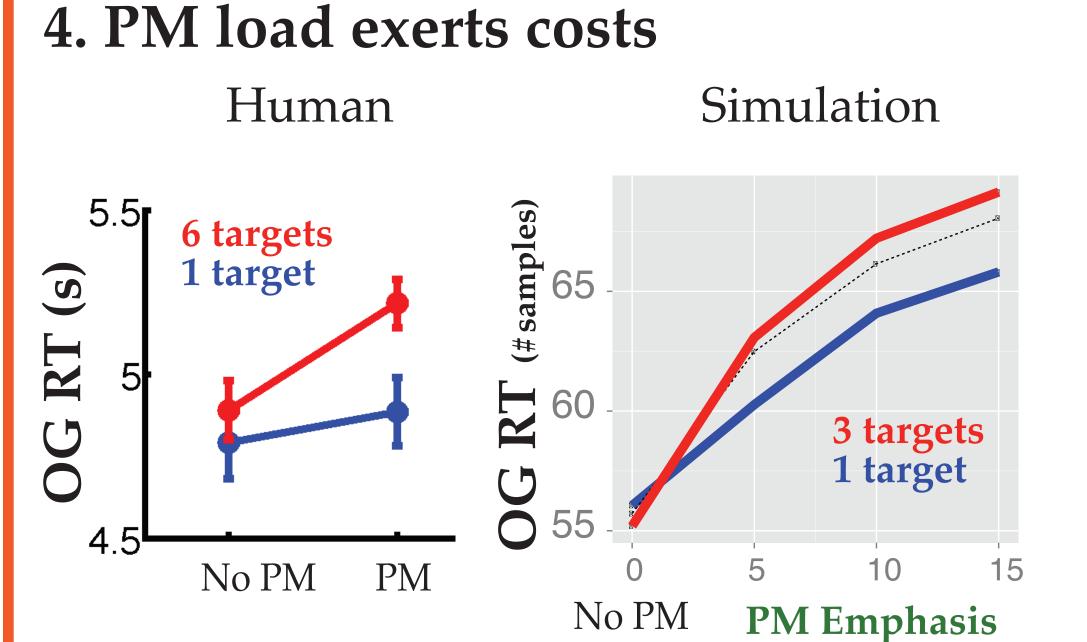
The Bayesian integration naturally weighs information in WM & EM as a function of the uncertainty of memory encodings. When episodic memory (EM) interference is high, weighing EM does not pay off. When WM is noisier (e.g. due to high load) weighing WM does not payoff. Thus, value optimization & match uncertainty control WM-EM tradeoff.

Findings: Human behavior vs. model simulation

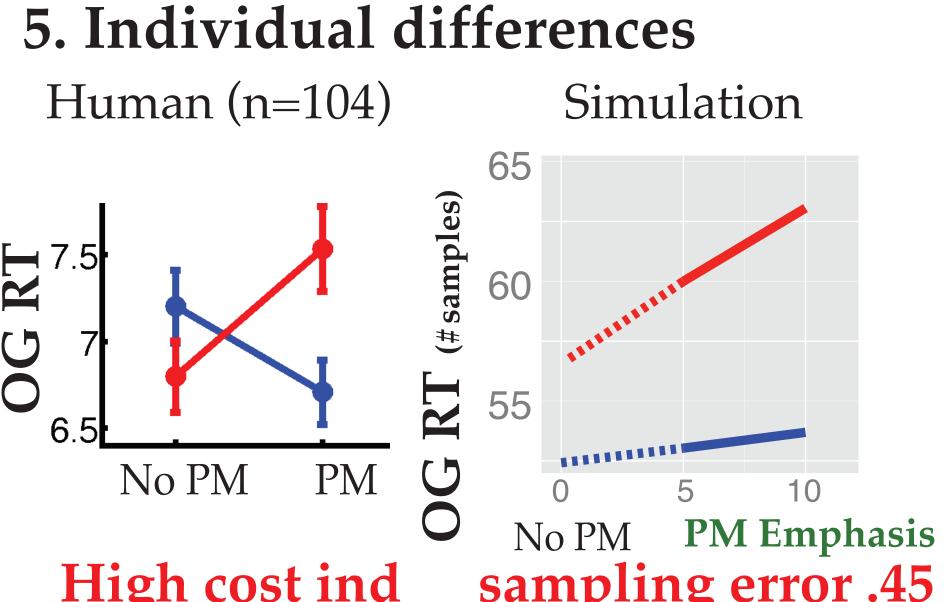


ongoing task Focality X PM payoff effects 3. Prediction: WM use





1 & 2.



sampling error .45 High cost ind sampling error .25 Low cost ind Rational control: We propose a normative model to strike the optimal balance

between WM & EM to maximize value given varying perceptual noise, load, & payoffs. The model simulates human findings on the simultaneous execution of immediate & delayed tasks & makes novel predictions. Model can be extended to other tasks with noisy memory & perception. It can help

(0=no PM)

empirically compare WM-EM interaction in cognition, & identify the bounded rationality of semingly suboptimal actions.

Human data: Einstein, G. O., McDaniel, M. A. et al. (2005). Multiple processes in prospective memory retrieval: factors determining monitoring versus spontaneous retrieval. JEPG.

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