Working memory constructs joint probabilistic task representations for decision-making

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Abstract:

The human brain has a remarkable ability in extracting and integrating relevant data for guiding actions and decisions. This capacity in part depends on working memory (WM), which maintains and manipulates task-relevant information in the service of goal-directed behavior. Theories and experimental evidence suggest that the mnemonic mechanisms of WM functions probabilistically, implying its potential to form a joint distribution for integrating multiple working memory representations. Yet, it remains an open question whether this probabilistic operation underpins the WM process in constructing task representation for guiding decisions, especially in the presence of multiple WM inputs. Our study investigates whether WM integrates multifaceted information probabilistically or deterministically. We designed a novel task requiring subjects to make decisions based on multi-dimensional WM content, with four levels of ambiguity associated with each dimension of WM features. We observed that response time and error rates increase with the cumulative ambiguity of WM representations. Through computational modeling, we found that a probabilistic model, which integrates WM uncertainty, outperformed deterministic models. This suggests that WM likely employs a probabilistic operation to integrate multiple representations, guiding decision-making.

Keywords: working memory; task representation; decision making; integration; cognitive control

Introduction

In daily life, we constantly select and integrate relevant information to guide decisions. Such process is facilitated by working memory (WM), a cognitive facility that temporarily holds and manipulates information planning future action and decision-making (Baddeley & Wilson, 2002). Information held in WM is encoded as a probabilistic distribution, representing both the memorized content and uncertainty (Li et al., 2021; Ma et al., 2006).

Despite these insights into WM's mnemonic mechanisms, how WM integrates multiple WM representations and its uncertainty is not well understood. Specifically, it is unclear how uncertainty in WM representations shape decision-making, particularly when facing multifaceted noisy inputs. Our hypothesis is that WM integrates information probabilistically, considering the uncertainty of task-relevant features to construct a posterior probabilistic task representation to guide decisions. Alternatively, WM may operate with a deterministic strategy that establishes rigid decision boundaries to dismiss low-probability information (Figure 1a). Our study employed computational models to test these two competing accounts.

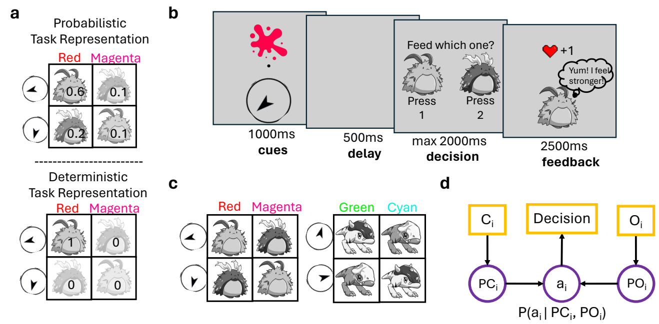

Figure 1. (a) Probabilistic task representation vs. deterministic task representation; (b) Feeding procedure; (c) Two lookup tables; (d) Computational modeling for testing phase.

Method

Twenty-one human subjects (12 females; age range: 18-35) participated in our experiment. The study protocol was approved by our IRB (#201808855).

Behavioral Paradigm

A game was designed as the behavioral paradigm. In the game, participants took on the role of zookeepers, tasked with ensuring the well-being of four artificial animals by catering to their dietary preferences. Participants first observed two cues on the appearance (color) and location (orientation) of food, using this information to judge the correct animal to feed based on provided feedback (Figure 1b). Notably, understanding either color or orientation alone is insufficient for making accurate feeding decisions. In the initial training phase, participants were acquainted with each animal's appetites, aiming to develop two task representations of lookup tables (Figure 1c). As the study progressed to the testing phase, the core task remains, but participants encountered varying levels of ambiguity in both color and orientation cues. This setup aims to explore whether working memory integrates ambiguous sensory information in a probabilistic or deterministic manner to make decisions. To achieve this, we introduced four levels of ambiguity for both color and orientation by adjusting the proximity of the presented color to the preferred food color on the HSV-space color wheel, and by altering the presented orientation to the preferred food orientation on the circle. We employed a full cross-factorial method to systematically evaluate the effect of these combined ambiguities on the decision-making process.

Computational Models

We first applied a ***reinforcement learning model*** to estimate each subject's learning outcome of task representations, specifically the likelihood of correctly choosing an animal given specific color and orientation cues. Starting with a uniform prior distribution to represent initial beliefs, the model iteratively updated its predictions by incorporating feedback from each trial via the learning rate parameter α:

$$P_{i+1}(a|C_i, O_i) = \begin{cases} P_i(a|C_i, O_i) + \alpha\big(1 - P_i(a, C_i, O_i)\big), if\ a = a_i^1 \\ P_i(a|C_i, O_i) + \alpha\big(0 - P_i(a, C_i, O_i)\big), if\ a = a_i^2 \end{cases}$$

where a_i^1 and a_i^2 are the correct and paired animal on trial i, respectively. C_i and O_i refer to the color and orientation presented on trial i.

The participant's decision modeled using a softmax function:

$$\Delta P = P_i\big(a_i^1|C_i, O_i\big) - P_i\big(a_i^2|C_i, O_i\big)$$
$$P_{choice} = logit(\beta_0 \Delta P + \beta_1 F_1 + \beta_2 F_2)$$

We then used a ***probabilistic model*** to capture human decisions with the premise that WM probabilistically integrates dual inputs (Figure 1d). For each trial, the probabilistic model maintains probabilistic distribution conditioned on the presented color/orientation:

$$P(C_i|PC_i) \sim von\ Mises(C_i|PC_i, \kappa_c)$$
$$P(O_i|PO_i) \sim von\ Mises(O_i|PO_i, \kappa_o)$$
$$P(C_i, O_i|PC_i, PO_i) = P(C_i|PC_i) \times P(O_i|PO_i)$$

Where PC_i and PO_i are presented color and orientation on trial i, respectively. Crucially, the belief of choosing each of the two animals based on the presented stimuli was calculated by integrating all color-orientation combinations from the training phase:

$$P(a_i^1|PC_i, PO_i) = \sum_{c,o} P(a_i^1|C_i, O_i)\, P(C_i, O_i|PC_i, PO_i)$$
$$P(a_i^2|PC_i, PO_i) = \sum_{c,o} P(a_i^2|C_i, O_i)\, P(C_i, O_i|PC_i, PO_i)$$

The decision making and updating of $P_{i+1}(a|C_i, O_i)$ are identical to the learning phase. Free parameters κ_c, κ_o, β_0, β_1, β_2 were estimated using maximum likelihood estimation.

We developed three types of ***deterministic models*** to explore whether working memory process information probabilistically or deterministically. This includes one fully deterministic model, wherein both probabilistic distributions $P(C_i|PC_i)$ and $P(O_i|PO_i)$ became deterministic using a winner-take-all procedure. We also added two partially deterministic models with only the color or the orientation was deterministic.

Results

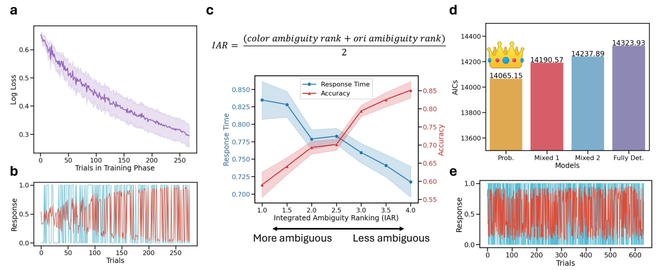

Figure 2. (a) Trial-wise log loss averaged across 21 subjects in the training phase; (b) One example of learning model performance; (c) Integrated ambiguity modulates behavioral performance; (d) AICs among four computation models for testing phase; (e) One example of probabilistic model performance. (b)(d) Red color: model predicted response; blue color: actual response.

Task Representation Learning

The log loss analysis of the learning model revealed an improvement in model prediction across trials, suggesting that participants learned the task representations (Figure 2a&b).

Integrated Ambiguity Modulates Behavioral Performance

A two-way rmANOVA with color and orientation ambiguity (4 levels each) revealed significant interaction effects on both accuracy (F(9,180)=2.35, p=0.02) and response time (F(9,180)=1.17, p=0.02), suggesting the significant effect of WM integration on performance. Additionally, significant variations in accuracy (F(6,120)=50.85, p < 0.0001) and response time (F(6,120)=9.20, p<0.0001) were observed as a function of the integrated ambiguity (Figure 2c).

Probabilistic Model Outperforms Deterministic Models

The probability model best predicted the subject's response and demonstrated the lowest AIC values among the four competing models (Figure 2c&d). Protected exceedance probability analysis strongly favored the probabilistic model (protected exceedance probability=0.9996, Bayes Omnibus risk= 1.9853e-05).

Conclusion

Working memory constructs task representations for decision making by incorporating the uncertainty of task-relevant working memory representations.

Acknowledgments

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