Dynamics of Multi-form Task Representations during Sequence Learning

Guochun Yang (guochun-yang@uiowa.edu)
Department of Psychological and Brain Sciences, University of Iowa,
340 Iowa Avenue, Iowa City, IA 52242 USA

Jiefeng Jiang (jiefeng-jiang@uiowa.edu)
Department of Psychological and Brain Sciences, University of Iowa,
340 Iowa Avenue, Iowa City, IA 52242 USA

Abstract:

While humans can rapidly learn new tasks, the underlying task representations are less known. We posited that a task, such as cooking, might be conceptualized in various formats—either as a sequence of steps (sequence-form), a collection of discrete tasks (task-form), or as interconnected subtasks linked by transitions (transition-form). To probe these ideas, we designed a delayed matching paradigm where participants were required to remember a stimulus composed of five distinct features and then select the matching option for a prompted feature after a brief interval. Five trials form a sequence, each having a fixed order of cued features. A good memory of sequence/transition can predict the upcoming task and enhance performance. We tested the dynamics of different representational forms by training participants (n = 37) with varying combinations of sequences at different stages. We developed a model with a hidden variable for each representational form. Model comparison results supported the presence of representations in different forms and characterized their dynamics in learning. In summary, our findings underscore the dynamic changes in task representation during learning.

Keywords: task representation; learning; computational modeling; sequence memory

Introduction

Our daily activities often comprise a series of routine steps. Take, for instance, the process of cooking a dish, which includes preparing ingredients and spices, heating, frying, among other steps. Mastery of these steps enables individuals to not only predict subsequent actions easily, but also to execute recipes including similar steps. However, when a chef must deal with multiple cooking tasks simultaneously, the sequences may interfere with each other and cannot be easily accessed.

Previous research has suggested a hierarchical representation structure for higher-order processing, such as cognitive control. For instance, Vaidya et al. (Vaidya & Badre, 2022; Vaidya et al., 2021) suggest that the human prefrontal cortex organizes task representations hierarchically, with the more rostral part encoding more abstract aspects and the more caudal part dealing with more concrete aspects. In a similar vein, Postle and Oberauer (2022) have delineated between declarative and procedural working memory, proposing a divergence in the representation of sequences and contents. Furthermore, Trach et al. (2021) have demonstrated that, with practice, the sequence-level representation of abstract tasks can strictly influence the sequence of concrete motor responses mediated by subtasks but not vice versa, suggesting a mixed hierarchy during sequential task implementation. Drawing on these insights, we hypothesize the existence of various formats of task representations, encompassing sequence, task, and transition forms (i.e., encoding part of the sequence). More importantly, we aim to investigate whether the prominence of these representations is modulated by the task demand at hand.

To this end, we designed a series of task sequences containing transitions of different training frequencies. We trained participants on different sequences at varying stages. Our findings provide evidence for all three types of representations and reveal a dynamic modulation in the strength of these representations as training progresses.

Materials and Methods

Experimental Design

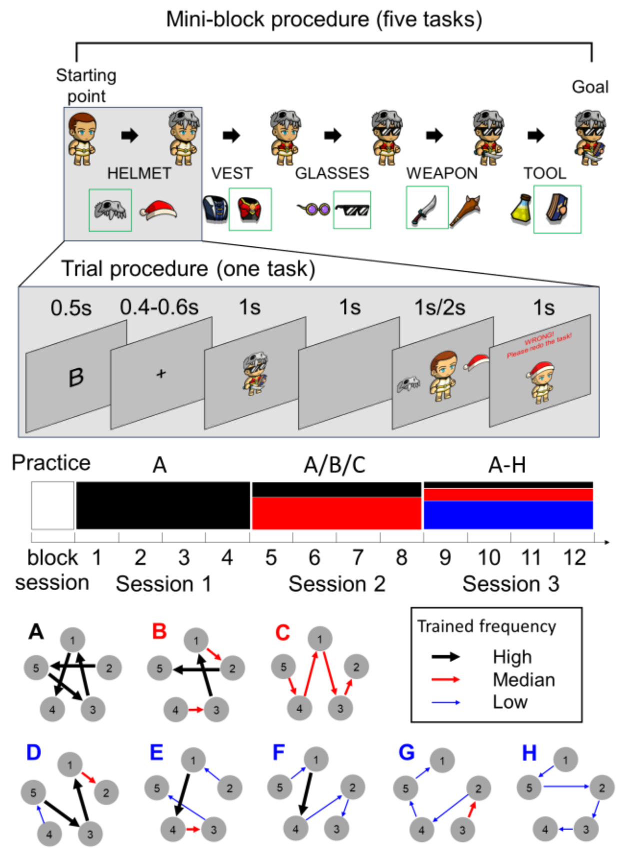

Figure 1. Task design and training procedure. The top panel shows the mini-block and trial procedures. The middle panel shows the procedure of three main training sessions. The bottom panel shows the eight different sequences used in different sessions, with arrow color and thickness indicating varying training frequencies.

We enrolled 37 young healthy participants (18-35 years old, average of 22.6 ± 4.2 years; 18 females). They were asked to perform multiple 5-trial mini-blocks to equip an avatar with gears based on a goal image (Fig. 1, top panel). Each trial started with a sequence cue (500ms), succeeded by a fixation (400-600ms), a goal image (1000ms), a blank screen (1000ms), a gear selection screen (2000ms if rt >= 1000ms, 1000ms if rt < 1000ms) and a feedback (1000ms). Error trials will be repeated until they are corrected (repetition trials). Participants were asked to respond to the gear selection screen with "F" and "J" keys as quickly and as accurately as possible.

There were one practice block with 20 trials and 12 formal blocks with 60 trials each. The formal blocks can be divided into three sessions, each with four blocks. The sequence cue varies in different sessions. In the practice block, the sequence cue was “X”, indicating a random sequence, whereas the sequence cues in the first/second/third session were “A”, “A”-“C”, and “A”-“H”, respectively, with each sequence equally distributed within each session (Fig. 1, middle and bottom panels).

Computational Model

Both RTs and ERs were collected. To delve into the different task representations and their impact on behavioral performance, we constructed a computational model positing distinct state variables for each level of representation within memory (Fig. 2A). These variables range from 0 to 1, are presumed to strengthen with repeated exposure to the same tasks, sequences, or transitions, and weaken over time due to forgetting. This dynamic is modeled via learning (α) and forgetting (β) rates. Specifically, the sequence representation is conceptualized as an 8x1 vector, with each element corresponding to a task sequence. An example of the hypothetical change dynamics of sequence representational strength is shown in the inset of Fig. 2A. The transition representation takes the form of a 5x5 matrix, denoting the likelihood of transitioning from one task to another. The task representation, akin to the sequence, is represented by a 5x1 vector, with each entry denoting the strength of each task. In addition, we also include a gating factor (termed as task exclusion, T_{exl}) that excludes completed tasks from the pool of remaining tasks within each mini-block. This factor will lead to a load effect in which performances of later steps are better than earlier steps. The task/sequence representations and the gating factor determine the entropy of predicting the upcoming task, thereby influencing behavioral performance, whereas the task representation strength directly influences behavioral performance. The entropy and task representation are submitted to a regression to predict the behavioral performance (both RT and ACC), and parameters (i.e., α and β for sequence/transition/task and T_{exl}) are optimized through minimizing the overall AIC of the regression models (Fig. 2A).

Results and Discussion

We tested eight nested models that involve different combinations of representation forms (Fig. 2B). Model comparison results suggest that the full model performs the best, *p*s < .001, thereby providing robust evidence for the presence of all the three representations. The accuracy of this model is evidenced by its ability to align predicted RTs closely with the observed RTs. Specifically, it mirrors the initial decline in the task load effect (slower RT for earlier steps) in blocks 3-4 compared to blocks 1-2, $t(36) = -7.11$, $p < .001$, followed by an increase in blocks 5-6 ($t(36) = 4.12$, $p < .001$), and a relatively stable pattern in blocks 6-12 (Fig. 2D), *p*s > .11.

In addition, to assess the role of task-form representation, we analyzed the regression coefficient for the task representation and conducted a one-sample t-test. Results showed that the stronger task representation is related to smaller RT, $t(36) = -4.39$, $p < .001$. This suggests the engagement of strong task-form representation (Fig. 2C).

In conclusion, our results support the existence of the three representational forms that all significantly influence task performance. Furthermore, our findings illuminate the dynamic nature of these representations, revealing how experience can influence these cognitive structures over time.

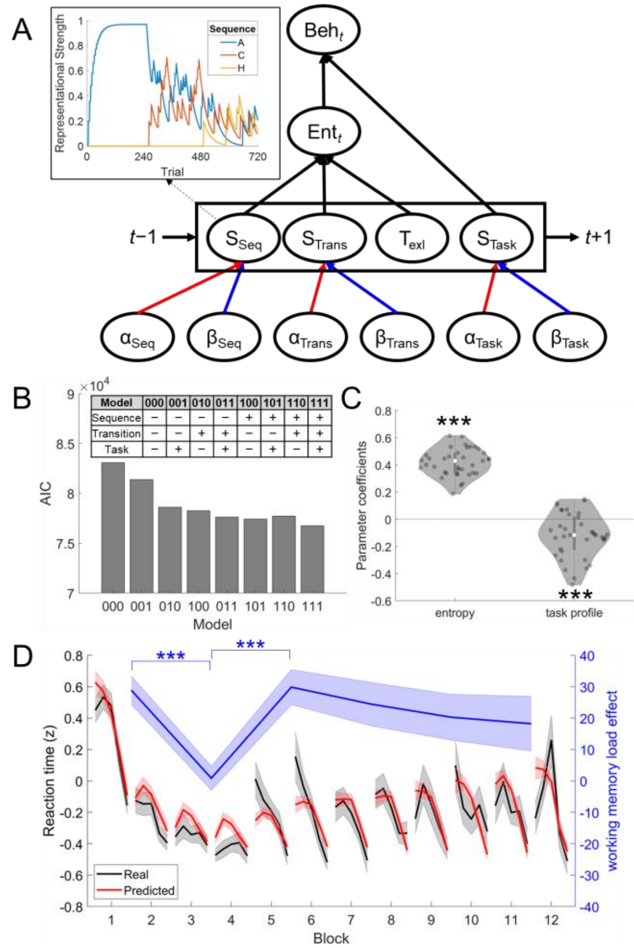

Figure 2. Computational model and results. A) The computational model posits a dynamic change of each representational format, which predicts the behavioral performance. The inset illustrates the hypothetical change of the representational strength for sequence-form with learning. B) The comparison between eight alternative models, with the three numbers in the model indices (e.g., 111) suggesting whether sequence /transition/task representations are included in the model. C) Parameter coefficients for entropy and task representation, two key regressors in the model fitting. D) Predicted RT (red color) overlaid with real RT (black color) for sequence A. The blue colored line shows the changing working memory load effect with learning.

Acknowledgments

This project was supported by the National Institute of Mental Health (R01MH131559 to J.J.).

References

Postle, B. R., & Oberauer, K. (2022). Working memory. In The Oxford Handbook of Human Memory. Oxford Univ. Press. In press Oxford, UK.

Trach, J. E., McKim, T. H., & Desrochers, T. M. (2021). Abstract sequential task control is facilitated by practice and embedded motor sequences. J Exp Psychol Learn Mem Cogn, 47(10), 1638-1659. https://doi.org/10.1037/xlm0001004

Vaidya, A. R., & Badre, D. (2022). Abstract task representations for inference and control. Trends Cogn Sci, 26(6), 484-498. https://doi.org/10.1016/j.tics.2022.03.009

Vaidya, A. R., Jones, H. M., Castillo, J., & Badre, D. (2021). Neural representation of abstract task structure during generalization. Elife, 10, 1-26. https://doi.org/10.7554/eLife.63226