Greater sensitivity of hippocampus and striatum to visual statistical learning in adults compared to children

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Abstract:

Statistical learning is the ability to learn statistical patterns in the environment. While statistical learning in the visual domain improves over development, the role of the implicit and explicit memory systems centered on the striatum and hippocampus is unclear. Using multivoxel pattern analysis, we investigated the functional role of the striatum and hippocampus in visual statistical learning. We trained multiple linear support vector machine classifiers to discriminate between deterministic/structured and non-deterministic/random triplets in the presented visual stimuli across the two brain structures for both linguistic and non-linguistic stimuli. Our results indicate distinct spatial patterns for structured and random triplets in adults (ages 18–24 years) across both the hippocampus and striatum, with similar performance across linguistic and non-linguistic domains. However, children (ages 6–12 years) do not show distinct spatial patterns across structured and random triplets for these two structures. These findings suggest that the hippocampus and striatum are less sensitive to temporal statistical regularities in visual stimuli in children than in adults, providing insights into the functional roles of the two memory systems in visual statistical learning over development.

Keywords: Statistical learning; functional magnetic resonance Imaging (fMRI); Multivoxel pattern analysis (MVPA); memory systems

Introduction

Humans' ability to learn statistical regularities in the environment is termed statistical learning (SL). Previous studies indicate improved SL abilities across development (Conway, 2020; Forest et al., 2023). Understanding the neural mechanisms of statistical learning and the underlying neurocognitive systems has been challenging. Specifically, the role of the implicit and explicit memory systems in statistical learning over development is unclear. Several studies show activations in the prefrontal cortex, sensory cortices, hippocampus, and striatum in statistical learning tasks (Batterink et al., 2019; Forest et al., 2023; Turk-Browne et al., 2009). However, the activations across the hippocampus and striatum have been inconsistent across studies, more so, in SL studies in children (Forest et al., 2023). Some of these inconsistencies can be attributable to the low sensitivity of the traditional univariate approaches, variability in sample age ranges, and inter-individual variability in brain activation patterns in SL tasks.

Multivoxel pattern analysis (MVPA) or decoding analyses utilize distinct spatial patterns in brain activity to differentiate between stimuli conditions (Mahmoudi et al., 2012; Tong & Pratte, 2012). In contrast with the mass-univariate approaches, MVPA is more sensitive to condition differences and can account for inter-individual variability in activation patterns across subjects.

Study

We use decoding analyses with fMRI data obtained from adults and children exposed to a visual SL task to investigate the role of the hippocampus and the striatum in visual SL across development. Because adults are more experienced in language than children, we also investigate whether the group differences vary across the linguistic and non-linguistic domains. Higher decoding performance for an ROI indicates greater sensitivity of the ROI and more distinct spatial activation patterns in response to the temporal structure of the visual stimuli.

Methods

Participants We used a task-based, child-friendly visual SL fMRI protocol to obtain neuroimaging data from 22 children (age M = 8.6 years, SD = 2.1; 12 Female, 9 Male, 1 Other) and 29 adult participants (age M = 20.3 years, SD = 1.3; 20 Female, 9 Male). Both the child and the adult participants were right-handed, native English speakers and had no history of any neurological or psychiatric disorders.

Stimuli and task: The participants were exposed to visual stimuli consisting of structured and random triplets of images of alien characters (non-linguistic) and alien characters holding up English letters (linguistic). The stimuli were organized into blocks of 48 stimuli (16 triplets) corresponding to one of 4 categories: letters (Ltr-Str) and images (Img-Str) with deterministic triplet structure, randomly ordered letters (Ltr-Rnd), and images (Img-Rnd). There were three blocks of a category in a run. Furthermore, two sessions (each session consisting of 2 runs) of the fMRI data were collected for each participant. Each session consisted of structured stimuli from one domain and random stimuli from the other domain. For example, as shown in Figure 1, if session 1 consisted of Ltr-Str and Img-Rnd, then session 2 consisted of Img-Str and Ltr-Rnd. The order of the sessions was counterbalanced across participants. Both the letter and the image triplets are learnable for adults, supported by faster response times to structured than random stimuli (Schneider et al., 2020).

fMRI data acquisition:fMRI data were acquired at two sites with a 64-channel phased array coil. Functional images were acquired using simultaneous multi-slice, T2*-weighted echo-planar imaging scans (TR=800 ms, TE=32 ms, flip angle=61°, FOV=21 cm, in-plane matrix=64 × 64, acceleration factor=6). We acquired 60 adjacent slices in an interleaved sequence resulting in volumes with 2.5 × 2.5 × 2.75 mm^3 resolution.

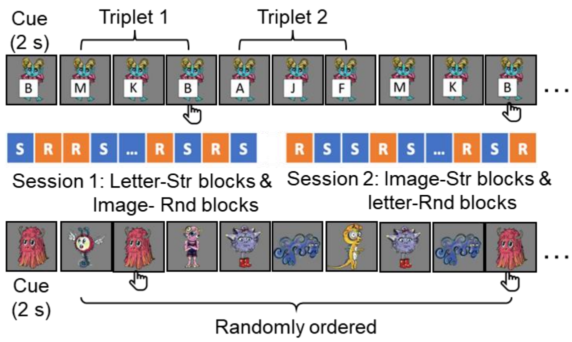

Figure 1: Schematic of the visual SL task.

Analysis

Preprocessing BOLD data was preprocessed using FMRIPREP (version 22.1.1) (Esteban et al., 2018). The preprocessing pipeline included slice time correction, motion correction, co-registration of the BOLD image with the T1w image, and normalization to the ICB 152 Nonlinear Asymmetrical template v2009c.

Furthermore, for the MVPA to account for baseline differences and variance in the BOLD activation across runs, the mean activation of the non-task blocks was subtracted from the BOLD data for each time point, and the time series data across each voxel was normalized to have a zero mean and SD of 1. The data from all the runs were concatenated as structured, and random conditions were distributed across the different runs.

Harvard-Oxford cortical and subcortical atlases were used to extract the two bilateral ROIs, hippocampus and striatum (caudate, putamen, and nucleus accumbens), used in this study.

Multi-voxel pattern analysis After concatenating the BOLD data across different runs, a linear-support vector machine classifier was trained on the linguistic and non-linguistic conditions separately to discriminate between time points corresponding to structured and random conditions. The area-under-curve for the receiver-operating characteristics (ROC) curve from a 10-fold cross-validation classification procedure was used to get estimates of the classifier performance.

Since the structured and random conditions are across different runs, we also trained a "no-task" classifier to classify the "rest blocks" across different runs. We use this classifier performance as a baseline as the linguistic and non-linguistic classifier may reflect "run" differences in addition to the condition differences. Hence, to control for the "run" differences, the classifier decoding results reported are obtained from the difference between the linguistic and non-linguistic classifiers and the "no-task blocks" classifier to just reflect condition differences.

Statistical Analysis Linear mixed-effect models were fit on the decoder performance measures with the ROI (hippocampus, striatum), domain (linguistic, non-linguistic), and group (child, adult) as fixed effects and the subjects as a random effect.

Results

In adults, the hippocampal and striatal decoding performance for the structured vs random conditions was significantly above the no-task classifier's performance across domains. However, children's hippocampus and striatum did not differentiate structured from random conditions better than the no-task classifier. A linear mixed-effect model on the performance scores yielded a statistically significant main effect of group ($z = -3.31$, $p < .001$) but no significant main effects for domain or ROI. Furthermore, no significant interactions were identified. Since there was no main effect of the domain, in Figure 2, we plot the pooled linguistic and non-linguistic decoding performances (with the no-task block decoding performance subtracted) for adults and children for both hippocampus and striatum. To summarize, the results seem to indicate that decoding performance was much higher in both ROIs for adults compared to children, and adults had statistically significant decoding performance attributable to condition discriminability.

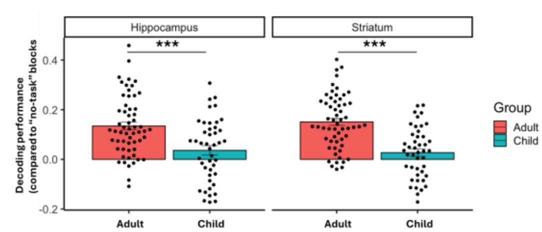

Figure 2: Decoder performance across adult and child attributable to structured vs random differences for hippocampus and striatum (*** $p < .0001$)

Discussion

The current work suggests that the hippocampus and striatum show distinct spatial patterns for structured and random visual stimuli in adults. These brain structures show similar performance in both linguistic and non-linguistic domains in adults. Children do not show such distinct spatial patterns for structured and random visual stimuli. Since previous studies seem to indicate that statistical learning in the visual domain improves across age (Arciuli & Simpson, 2011; Shufaniya & Arnon, 2018), we plan to conduct additional analyses to examine if the chance-level performance in children is due to their low-SL skills or the developmental trajectory of the hippocampus (Schlichting et al., 2017) and striatum. The latter possibility may indicate that these brain structures play a less critical role in statistical learning in childhood.

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References

Arciuli, J., & Simpson, I. C. (2011). Statistical learning in typically developing children: the role of age and speed of stimulus presentation. Developmental Science, 14(3), 464–473. https://doi.org/10.1111/J.1467-7687.2009.00937.X

Batterink, L. J., Paller, K. A., & Reber, P. J. (2019). Understanding the Neural Bases of Implicit and Statistical Learning. Topics in Cognitive Science, 11(3), 482–503. https://doi.org/10.1111/TOPS.12420

Esteban, O., Markiewicz, C. J., Blair, R. W., Moodie, C. A., Isik, A. I., Erramuzpe, A., Kent, J. D., Goncalves, M., DuPre, E., Snyder, M., Oya, H., Ghosh, S. S., Wright, J., Durnez, J., Poldrack, R. A., & Gorgolewski, K. J. (2018). fMRIPrep: a robust preprocessing pipeline for functional MRI. Nature Methods 2018 16:1, 16(1), 111–116. https://doi.org/10.1038/s41592-018-0235-4

Forest, T. A., Schlichting, M. L., Duncan, K. D., & Finn, A. S. (2023). Changes in statistical learning across development. Nature Reviews Psychology 2023 2:4, 2(4), 205–219. https://doi.org/10.1038/s44159-023-00157-0

Mahmoudi, A., Takerkart, S., Regragui, F., Boussaoud, D., & Brovelli, A. (2012). Multivoxel pattern analysis for fMRI data: A review. Computational and Mathematical Methods in Medicine, 2012. https://doi.org/10.1155/2012/961257

Schlichting, M. L., Guarino, K. F., Schapiro, A. C., Turk-Browne, N. B., & Preston, A. R. (2017). Hippocampal Structure Predicts Statistical Learning and Associative Inference Abilities during Development. Journal of Cognitive Neuroscience, 29(1), 37–51. https://doi.org/10.1162/JOCN_A_01028

Schneider, J. M., Hu, A., Legault, J., & Qi, Z. (2020). Measuring statistical learning across modalities and domains in school-aged children via an online platform and neuroimaging techniques. Journal of Visualized Experiments, 2020(160), 1–21. https://doi.org/10.3791/61474

Shufaniya, A., & Arnon, I. (2018). Statistical Learning Is Not Age-Invariant During Childhood: Performance Improves With Age Across Modality. Cognitive Science, 42(8), 3100–3115. https://doi.org/10.1111/COGS.12692

Tong, F., & Pratte, M. S. (2012). Decoding patterns of human brain activity. Annual Review of Psychology, 63(Volume 63, 2012), 483–509. https://doi.org/10.1146/ANNUREV-PSYCH-120710-100412

Turk-Browne, N. B., Scholl, B. J., Chun, M. M., & Johnson, M. K. (2009). Neural Evidence of Statistical Learning: Efficient Detection of Visual Regularities Without Awareness. Journal of Cognitive Neuroscience, 21(10), 1934–1945. https://doi.org/10.1162/JOCN.2009.21131