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4-2020

EEG reinvestigations of visual statistical learning for faces, scenes, and objects

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Behrendt, Mei Grace; Lim, P. Cheng; Halvorsen, Aaron T.; Kuntzelman, Karl; and Johnson, Matthew R., "EEG reinvestigations of visual statistical learning for faces, scenes, and objects" (2020). *UCARE Research Products*. 246.

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BACKGROUND

- In a previous study, we studied statistical learning (SL) to understand temporal and spatial patterns in our environment. E.g. word segmentation in speech¹, visual regularities²
- Auditory SL helps to understand how infants learn language
- In language acquisition, there are conditional probabilities. (E.g., “pretty baby:” *pre ty* more likely than *ty ba*)
- We use visual SL to associate patterns in the environment (E.g., chairs are located under tables, not above)
- One previous fMRI study found that items strongly bound via SL showed more similar patterns of brain activity after learning, compared to before learning. However, it is unclear what underlying neural processes drove this effect
- In this study, we aimed to replicate previous results to better understand visual SL

TASK DESIGN & STIMULI

Stimulus Pairing



STRONG PAIRS (predictive)
Transitional Probability 1.0
Item B followed Item A 100% of the time



WEAK PAIRS (non-predictive)
Transitional Probability 1/9
Item D followed Item C 11% of the time

- EEG data collection was used to monitor brain activity as items were viewed
- Participants viewed 3 item categories: faces, scenes, objects
- Pairs were balanced across item categories
- Participants did not know that items were part of a pair
- Images were presented for 100ms each
- Cover task: pressed a button when an item jiggled (infrequent)
- 10 healthy participants have been recruited so far (additional data collection is ongoing)

Post-Task Learning Test

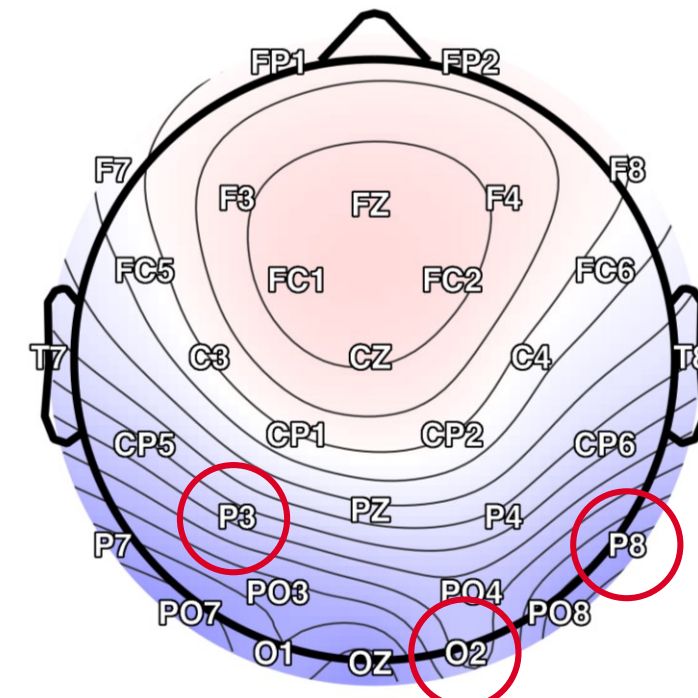


Very unfamiliar

 Very familiar

- Administered 5-10 minutes after main task completion
- 3 types of pairs presented: Strong pairs (TP 100%); Weak pairs (TP 11%); Foil pairs (TP 0%)
- Rated pair familiarity using a sliding scale

ERP RESULTS (PREVIOUS STUDY)



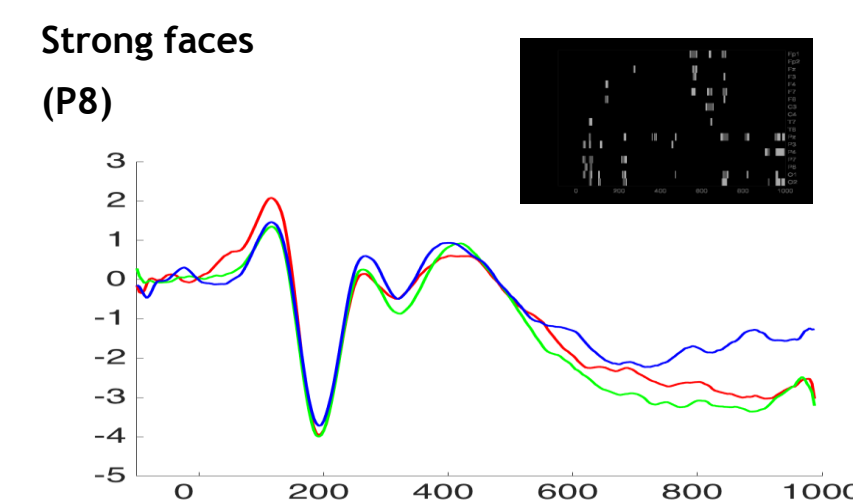
We recorded EEG from 32 electrode locations (shown left)

For this poster, we showed data for three sample electrodes (P8, P3, and O2; locations circled)

Listed below in each of the 6 plots are the uncorrected ANOVA statistics

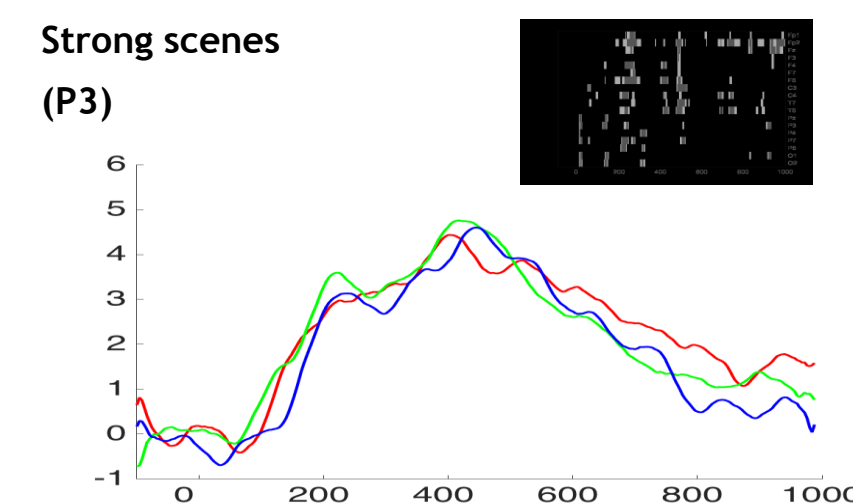
When the ANOVA statistics were corrected, there were no significant results

LEADING ITEMS IN STRONG & WEAK PAIRS, SPLIT BY UPCOMING ITEM



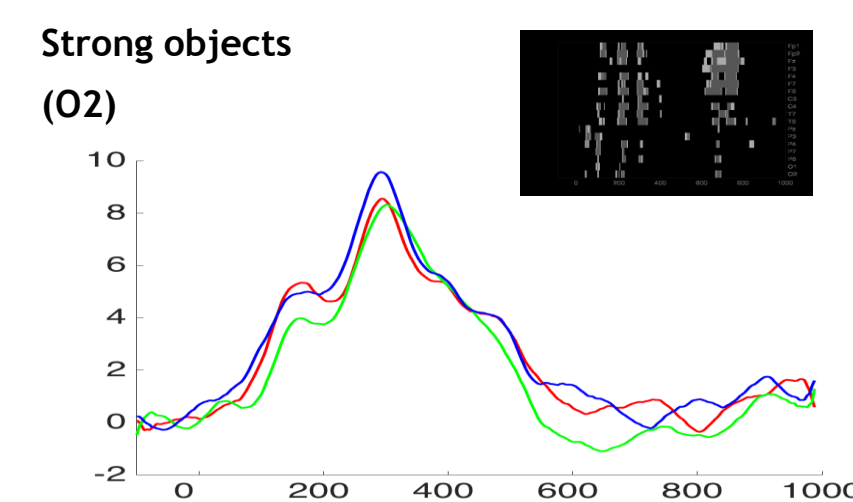
The plot took the first item in the strong pairs that looked at faces.

Deep learning accounted for 32.2%



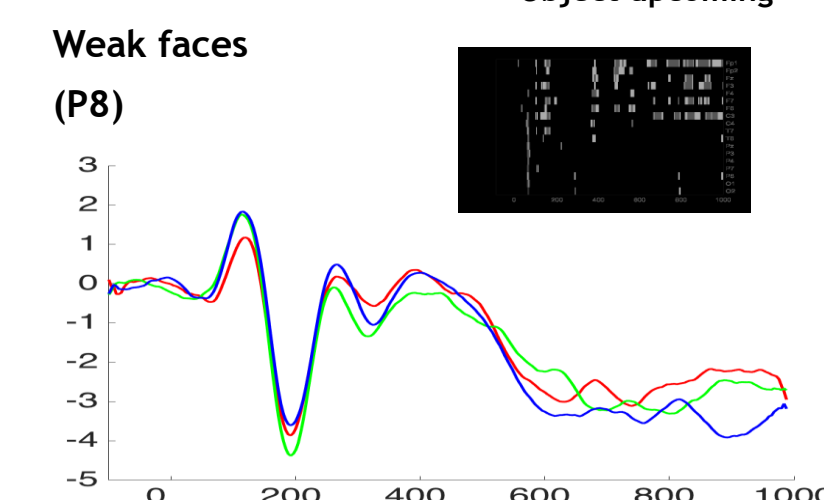
The plot took the first item in the strong pairs that looked at scenes.

Deep learning accounted for 35.5%*



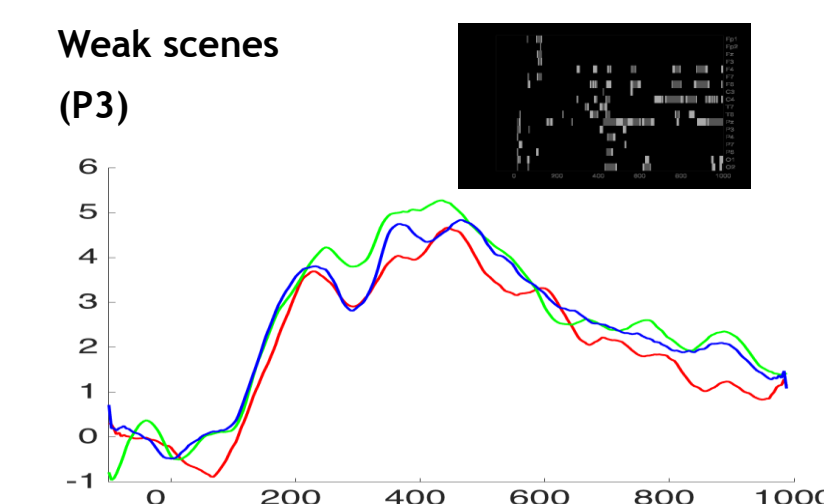
The plot took the first item in the strong pairs that looked at faces.

Deep learning accounted for 37.3%**



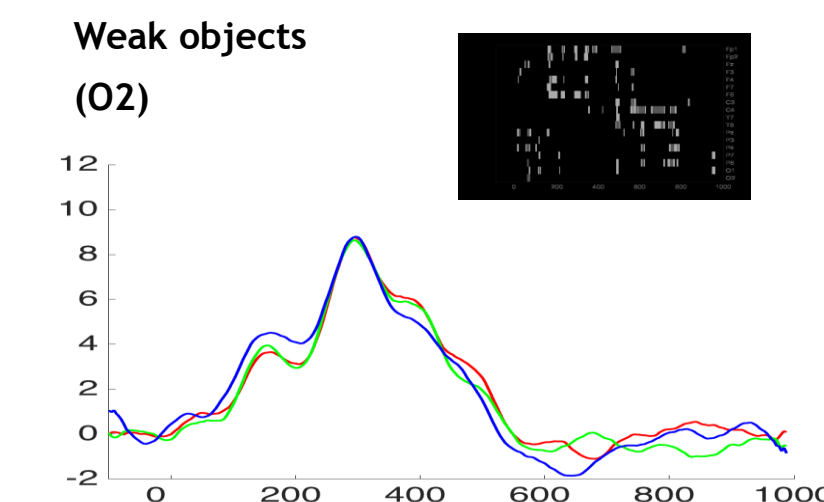
The plot took the first item in the weak pairs that looked at faces.

Deep learning accounted for 34.1%



The plot took the first item in the weak pairs that looked at scenes.

Deep learning accounted for 32.6%



The plot took the first item in the weak pairs that looked at faces.

Deep learning accounted for 33.0%

BEHAVIORAL RESULTS (CURRENT STUDY)

- We compared 3 types of item pairs:
 - Strong pairs (items appeared together 100% of the time; e.g. pair AB)
 - Weak pairs (items appeared together 11% of the time; e.g. pair CD)
 - Foil pairs (items appeared together 0% of the time; e.g. pair AC)
- We conducted a paired t-test, $\alpha = .05$, on the familiarity scores from the post-task learning test:
 - Strong pairs vs. weak pairs: $t(9) = 2.129, p = 0.062$
 - Strong pairs vs. foil pairs: $t(9) = 2.379, p = 0.041$
 - Foil pairs vs. weak pairs: $t(9) = -0.294, p = 0.775$

PREVIOUS ANALYSES

- Bandpass filter of 0.1 - 100 Hz applied after acquisition
- Automated and manual channel rejection using EEGLAB's spectrum measure (frequency range of 1-500)
- Automated trial-wise artifact rejection using ERPLAB; trials with peak-to-peak amplitude $> 100 \mu V$ in any electrode were removed from analysis
- Pre-stimulus baseline (100ms) average subtracted
- Trials binned by pair type (strong/weak) x item order (leading/trailing) x leading item category (face/scene/object) x trailing item category (face/scene/object)
- Convolutional neural network model run on ERP data classifying item category; trials that were correct $< 50\%$ of the time removed
- Previous analyses found behavioral differences between strong vs. foil and strong vs. weak pairs
- These results are similar with the current study ($n = 10$), which is promising and likely to replicate

CONCLUSIONS AND FUTURE DIRECTIONS

- Finish data collection and ERP statistics; if decoding fails, potentially consider adjusting experiment design
- Predictive items differentiate according to upcoming item. Does this become greater with more time or learning?
- Individual differences in post-task learning test; some people better at recognizing predictive/non-predictive items
- Do these people show more differentiation in predictive items?
- Machine learning: can we decode upcoming items while first item in pair is on screen?

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- Supported by UCARE and by NSF/EPSCoR grant #1632849 to MRJ and colleagues