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

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INTRODUCTION

- Statistical learning (SL) helps us learn about temporal/spatial patterns in our environment. E.g. word segmentation in speech[1], visual regularities[2]
- One previous fMRI study[3] 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
- The greater temporal resolution of EEG may allow us to detect prediction signals during SL that are not apparent with fMRI

TASK DESIGN & STIMULI

STIMULUS PAIRING

STRONG PAIRS (predictive)

Transitional Probability 1.0

Item B followed Item A 100% of the time

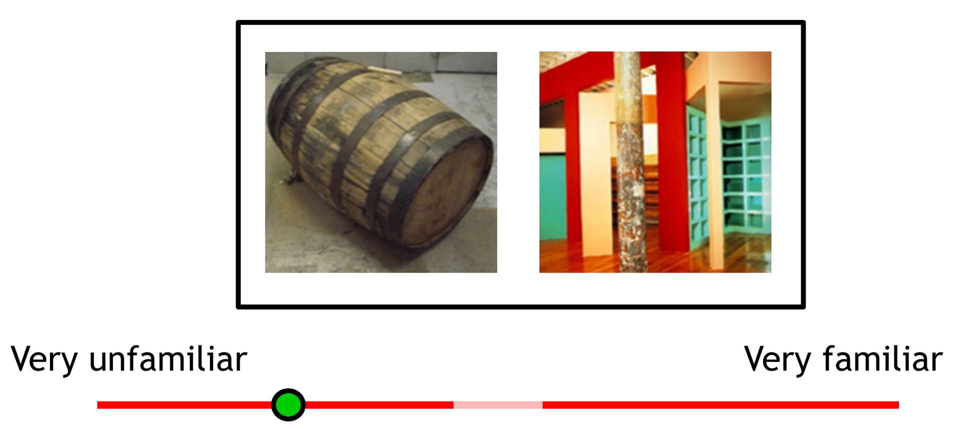
WEAK PAIRS (non-pred.)

Transitional Probability 1/9

Item D followed Item C 11% of the time

- 3 item categories used: Face, Scene, Object
- Unbeknownst to participants, all items were part of a pair
- Pairs balanced across item categories
- Images presented onscreen for 1000ms each
- Cover task: press button when an item jiggles (infrequent)
- EEG data collected on 256-channel EGI system
- N = 17 young, healthy subjects

POST-TASK LEARNING TEST

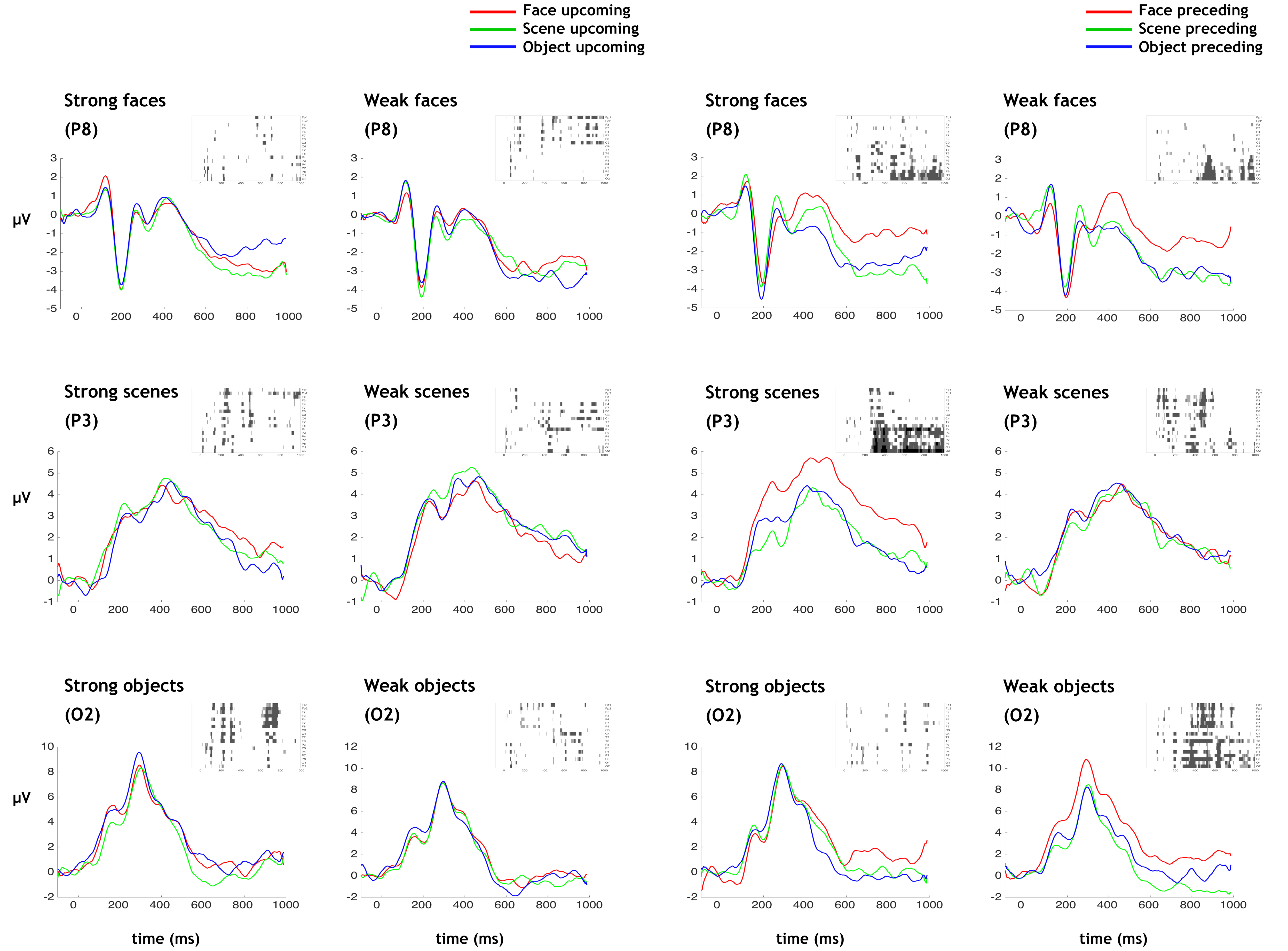


- Administered 5 minutes after main task completion
- 3 types of pairs presented: Strong pairs (TP 100%); Weak pairs (TP 11%); Foil pairs (TP 0%)
- Rated pair familiarity using sliding scale
- Strong pairs rated more familiar than weak pairs (p = .049) and foil pairs (p = .028)
- No difference between foil pairs and weak pairs (p = .937)

ERP RESULTS

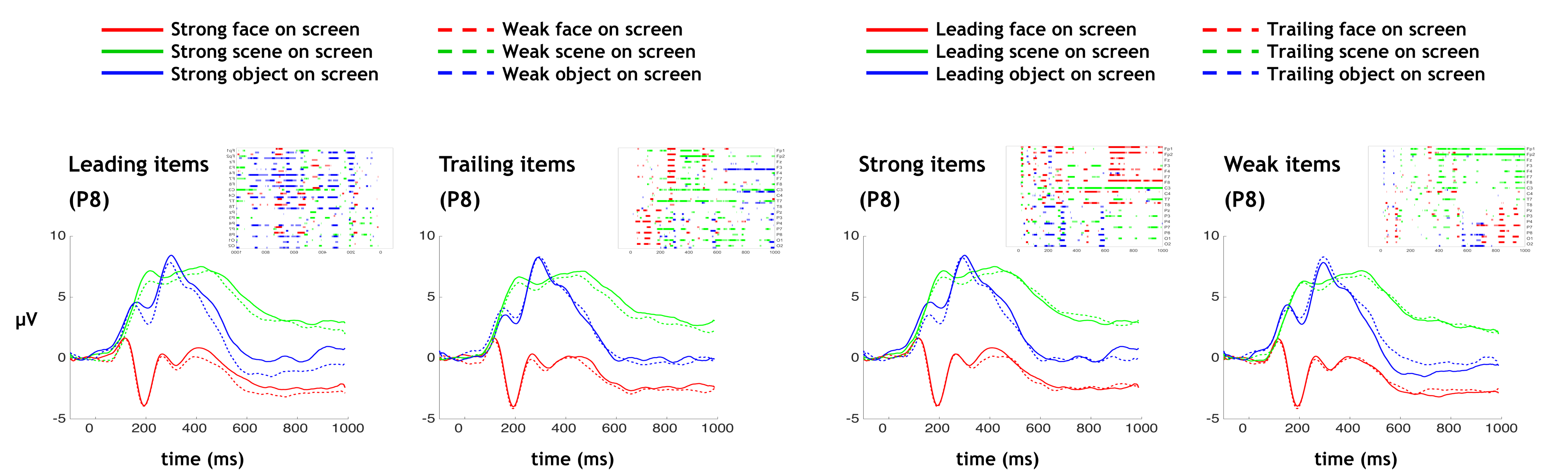
LEADING ITEMS IN STRONG & WEAK PAIRS, SPLIT BY UPCOMING ITEM

TRAILING ITEMS IN STRONG & WEAK PAIRS, SPLIT BY PRECEDING ITEM



LEADING & TRAILING ITEMS

STRONG & WEAK ITEMS



ANALYSIS METHODS

- 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)
- ERPLAB used for EEG preprocessing. 256-channel system converted to 10-10 system by averaging across electrode groups
- Convolutional neural network model run on ERP data classifying item category; trials that were correct <50% of the time removed

DEEP LEARNING RESULTS

CLASSIFY: UPCOMING ITEM (face/scene/obj; chance = 33.3%)

Leading items

Item	% acc
Strong faces	32.2
Strong scenes	35.5*
Strong objects	37.3**
Weak faces	34.1
Weak scenes	32.6
Weak objects	33.0

CLASSIFY: PRECEDING ITEM (face/scene/obj; chance = 33.3%)

Trailing items

Item	% acc
Strong faces	38.6**
Strong scenes	36.0**
Strong objects	34.1
Weak faces	36.4**
Weak scenes	36.2**
Weak objects	35.5*

CLASSIFY: PAIR TYPE (strong/weak; chance = 50%)

Item	% acc
Leading faces	49.6
Leading scenes	51.5**
Leading objects	50.1
Trailing faces	49.1
Trailing scenes	50.1
Trailing objects	51.4*

CLASSIFY: ITEM ORDER (leading/trailing; chance = 50%)

Item	% acc
Strong faces	50.2
Strong scenes	51.9**
Strong objects	50.9
Weak faces	48.3
Weak scenes	51.7**
Weak objects	48.8

one-sample t-test against chance: * p < .05; ** p < .001

CONCLUSIONS

- Some evidence that the EEG signal of learned (strong) items can be detected prior to their presentation, i.e. during item that predicts them
- Deep learning models may be able to detect effects that traditional ERP analyses cannot easily

REFERENCES & ACKNOWLEDGEMENTS

[1]Saffran JR, Aslin RN, Newport EL. 1996. *Science, 274*, 1926 - 1928
[2]Fiser J, Aslin RN. 2001. *Psychological Science, 12*, 499 - 504
[3]Schapiro AC, Kustner LV, Turk-Browne NB. 2012. *Current Biology, 22*, 1622 - 1627

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