Did you see that? Examining whether statistical learning can elicit category-specific EEG activity in the absence of visual stimuli

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Background

The present study used EEG with a statistical learning paradigm to examine if there were temporal effects at the trial-level.

Hypotheses:

1. Statistical learning will occur between audio and visual stimuli pairs.
2. Statistical learning will be observed in neural data
   A. There will be a mismatch negativity in trials where the expected image is not presented
   B. There will be a unique signal for trials where expected image is not presented
   C. The unique signal will be similar to the trials where the image is presented

Hardware

- Electrical Geodesics, Inc. 300-series amplifier
- 256-channel HydroCel Geodesic Sensor Net
- Recorded at 1000hz
- Average Referenced
- Bandpass filtered .1hz-30hz

Software

- **PsychoPy[1] -** Stimulus presentation software
- **PyNetstation module –** Python library for communicating with NetStation software
- **NetStation acquisition software -** EEG recording
- **MNE MEG/EEG toolbox[2,3] -** EEG data processing

Participants

- **14** participants were recorded, 5 are included in the EEG analyses (9 removed due to noise and lack of trials)

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Methods

Training

Participants were trained on a typical statistical learning paradigm. Groupings were in pairs between audio and visual stimuli.

- Audio stimuli were controlled syllables “ba”, “di”, “go”, etc.
- Visual stimuli were faces, objects, or no image.
- A 1000hz “click” sound was played at the presentation of potential visual stimuli (as a reference point).
- 792 trials total (audio and image):
  - 55 omitted image trials (image expected but not shown) for faces and objects each.
  - EEG analyzed to image trial onset (30 clean trials per participant).

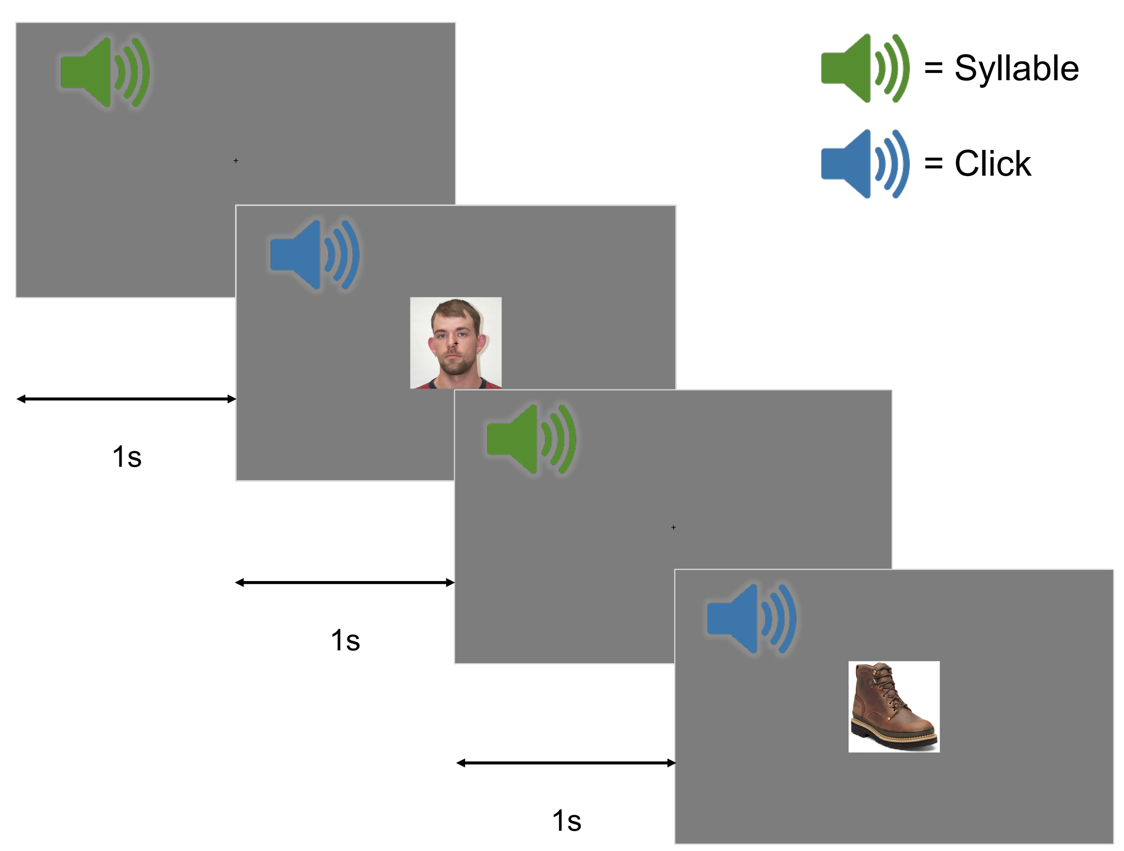

Figure 1. Sequence of events during two trials.

Testing

Participants were tested using typical 2 choice forced response task. The same stimuli pairs were tested with a randomized set of foil stimuli that were never seen before.

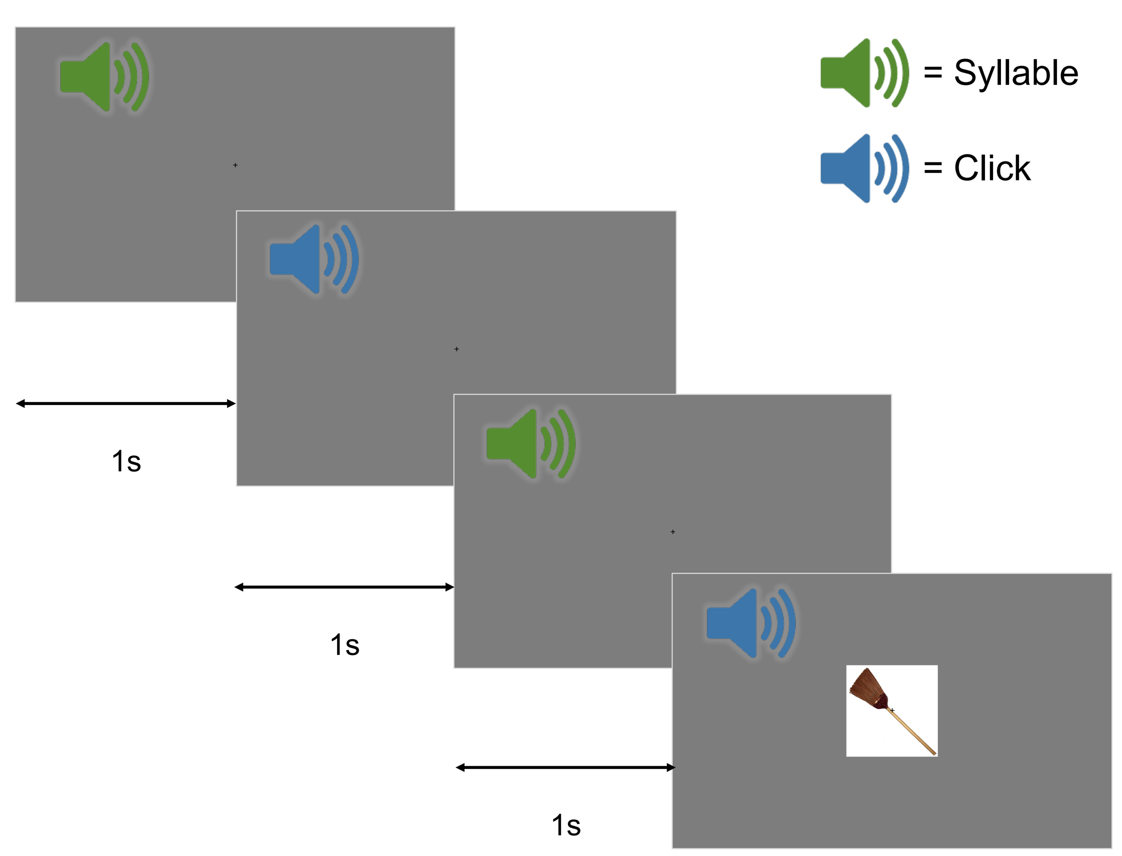

Figure 2. Sequence of events during a testing trial.

Results

1. Tests for statistical learning of audio/visual pairings showed no significant difference from chance ($p > .05$).
2. Findings suggest statistical learning was observed in neural data.
   A. A mismatch negativity was not observed in the trials where an image was expected but omitted (Fig. 3).
   B. A unique component was found between 85ms-125ms for omitted image trials (Fig. 4)
   C. Visual inspection suggests the unique component matches the deflection timing of the trials where images are presented (Fig. 4).

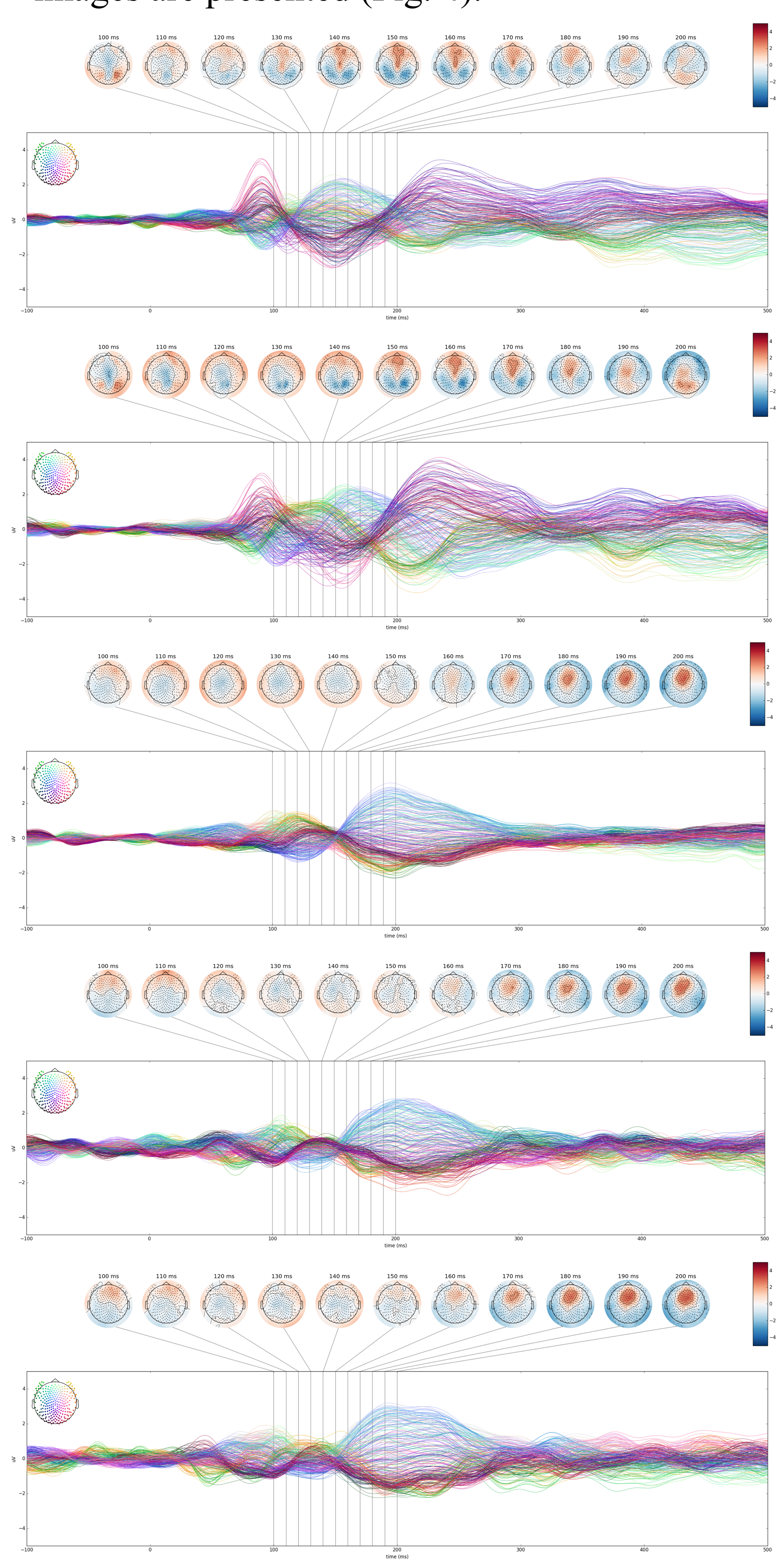

Figure 3. Topographic maps of electrical potential across the scalp at various points in the ERP waveform. Conditions from top to bottom: face image present, object image present, no image present, face image omitted, object image omitted.

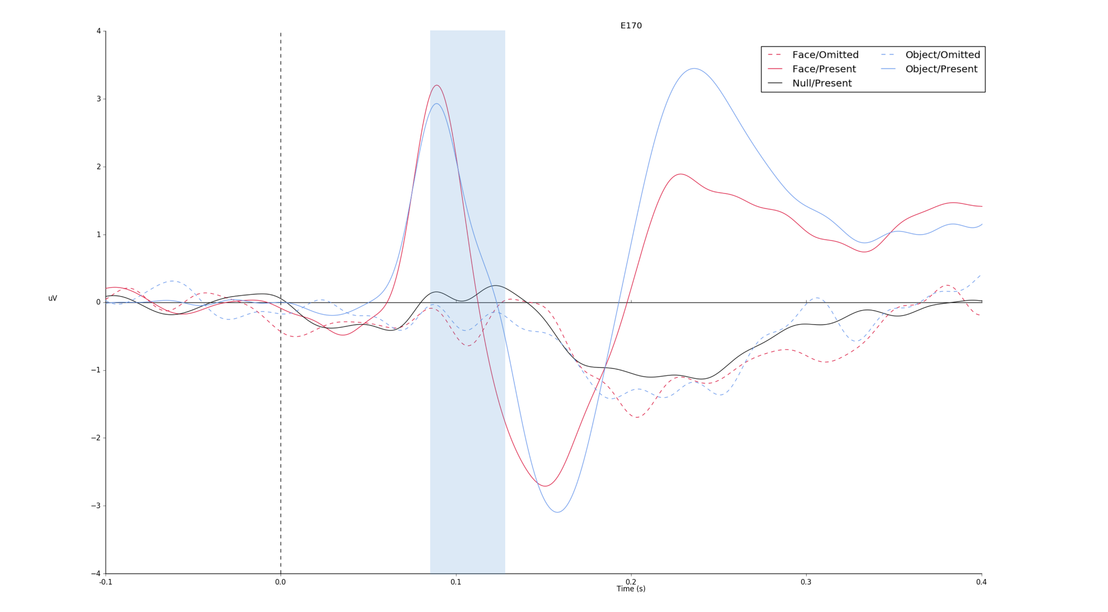

Figure 4. Plot of ERP’s for each condition of the experiment. Event start point is set to image onset time. The highlighted region shows the onset of the N170 component. The omitted image conditions show a matched trajectory to the N170. The peak amplitudes show a significant difference ($p < 0.001$) between the omitted image trials and the ”null” or no expected image trials.

Conclusions

- Findings suggest that we can potentially identify statistical learning in EEG signals.
  - More data needed for greater reliability in findings.
  - Different designs may validate these results.
- While current findings are preliminary, they suggest the existence of a “phantom N170” component in the omitted image trials.
- Differences between ”null” trials and ”omitted image” trials suggests implicit learning is occuring in participants.
- The abundance of trials may have an aversive effect on statistical learning paradigms.

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