Facilitating Creativity: Using Machine Learning EEG Classification to Provide Neurofeedback in a Divergent Thinking Task

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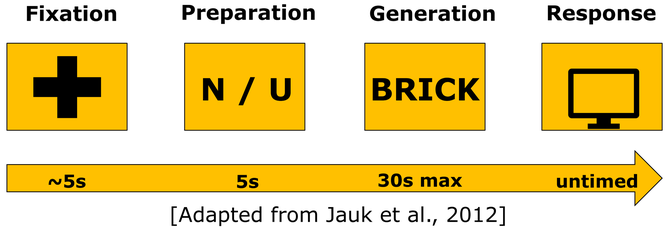
Background

- How is creativity defined?
  - Novel and useful idea generation [Sternberg & Lubart, 1999]
- What are the EEG characteristics of increased creativity?
  - Generally, increased alpha [Stevens & Zabelina, 2019]
  - Reduced attention to external stimuli [Fink & Benedek, 2014]
- How might machine learning be useful in this area?
  - Classification of more vs. less creative states…
  - … and more vs. less creative individuals

Current Study

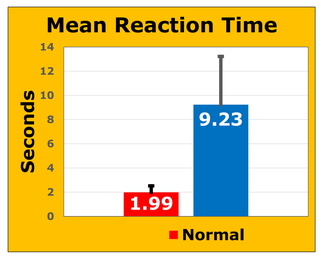
- Participants: N = 29
- We analyzed EEG data collected during an alternate use task [AUT]
  - Normal vs. Uncommon uses for objects
- Participants were presented with the following on a computer monitor for each trial:
  1. Fixation cross
  2. Cue word to indicate whether to think of a normal or uncommon way to use the upcoming object
  3. Name of an everyday object [pencil, brick, etc.]
  4. Blank space to enter a response



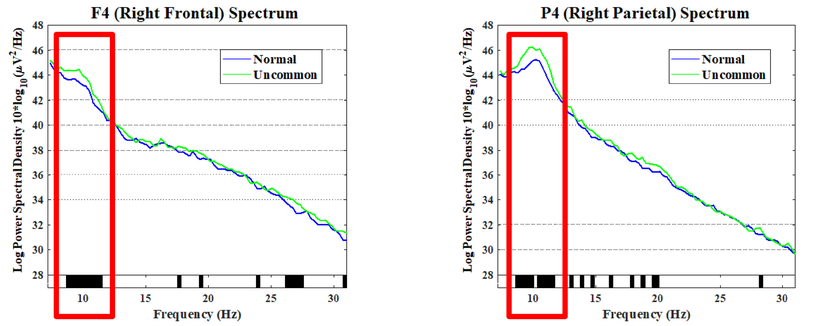
[Adapted from Jauk et al., 2012]

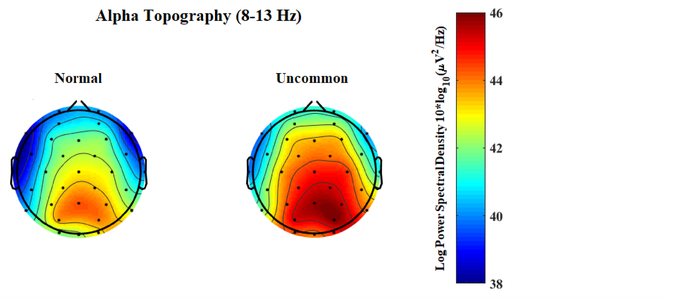
Results

- Responses were faster in the normal condition [M = 1.99s, SD = 0.53], compared to the uncommon condition [M = 9.23s, SD = 3.99, p < .001]



- Greater alpha power for Uncommon [p < 0.05]





Machine Learning Classification

- More and less creatively demanding conditions

- More and less creative people
  - Based on originality of responses
- BCILAB
  - MATLAB toolbox
  - Feature extraction
  - Quadratic Discriminant Analysis
  - 2 channels: F4 & P4
    - ➢ Lean input for rapid processing
      - ○ Assess feasibility of real-time feedback
      - ○ Limit less helpful channel data

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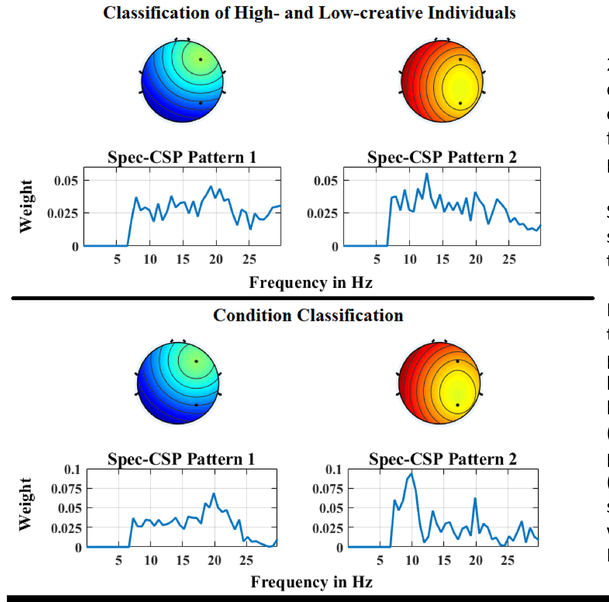
Classification Results

- Model training [10-fold cross-validation]
- Classification accuracy for the two conditions varied widely among individuals (36.7% to 93.3%)
- Mean condition accuracy = 63.9%
- For more vs. less creative individuals, 82.3% classification accuracy was attained



2 EEG channels (black dots) were used for classification: F4 (right frontal) and P4 (right parietal)

Spectral patterns are shown beneath the topographic maps

Relative to the rest of the spectrum, frontal patterns (upper and lower left side) exhibit heavily weighted beta (13-30 Hz), and parietal patterns (upper and lower right side) exhibit heavily weighted alpha (8-13 Hz)

Next Steps

- Use subjects' EEG data to train individualized condition classification models
- Provide real-time auditory feedback

- Analyses: Compare to previous participants [offline]
  - EEG differences?
  - More creative responses?

References

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