Towards user-centric brain-computer interface design: Unsupervised learning and Markov chain-based methods to understand user capabilities

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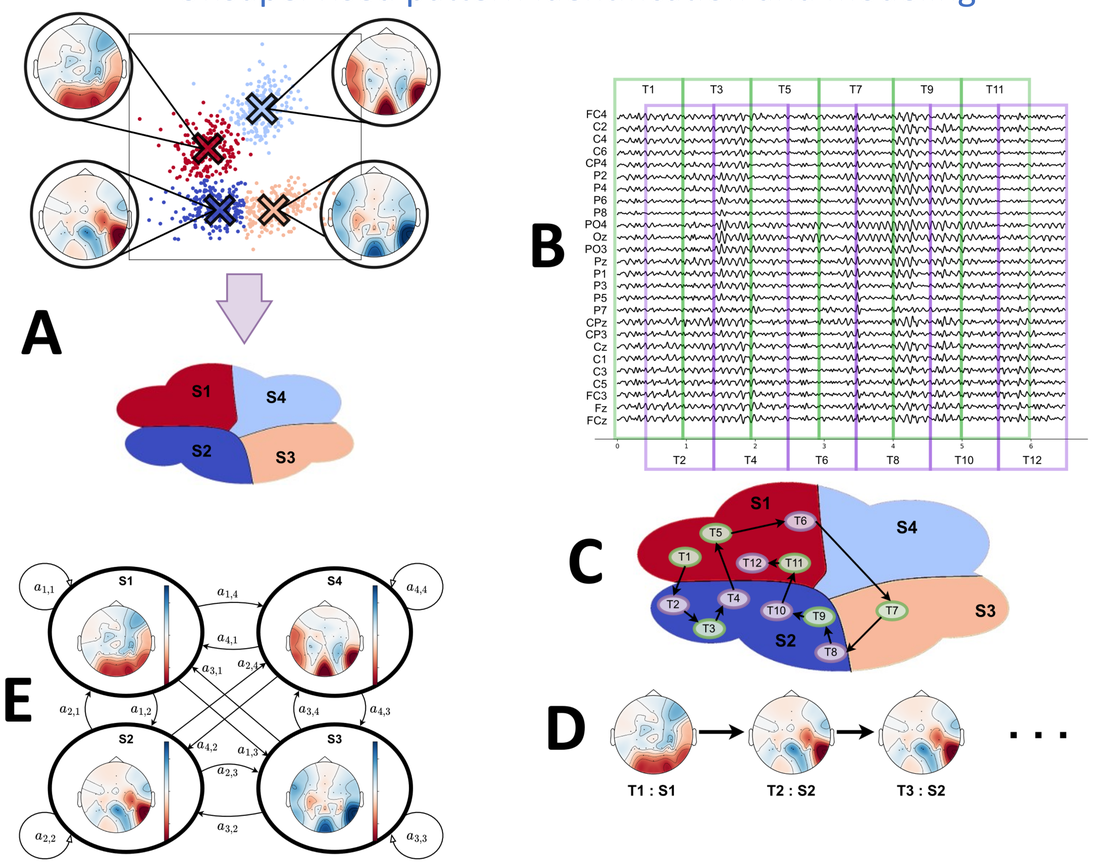
Introduction

- Brain-computer interface (BCI) use is limited by "**BCI Inefficiency**," where users struggle to produce brain signals that can be reliably recognized
- Potential solutions: improve user performance via training and/or optimize classifiers to better leverage user abilities
- Both approaches require **descriptive measures of user performance**
- Current classifier-based performance measures are limited
- With aim of describing user abilities, we designed two user-performance metrics formulated using pattern clustering and Markov chain models

Methods

Unsupervised pattern identification and modeling



A. Apply clustering methods to define state space of distinct pattern states that **users can produce, independent of task labels**
B. Segment trials into shorter temporal windows
C. Observe the pattern state for each temporal window
D. Represent trials as a stochastic sequence of pattern states
E. Model transitions between pattern states as a Markov chain

Performance metrics

$$taskDistinct = \sum_{i=1}^{N_t-1} \sum_{j=i+1}^{N_t} D_H(\pi^{(i)}, \pi^{(j)})$$

Measures ability to produce distinct patterns for different tasks

$$relativeTaskInconsistency = \frac{\frac{1}{N_c}\sum_{i=1}^{N_c} 1 + H_i}{1 + H_{rest}}$$

Measures (in)ability to maintain consistent pattern sequences

New models provide **descriptive information** about our **ability to control brain signals** and pave the way for user-centric brain-computer interface design

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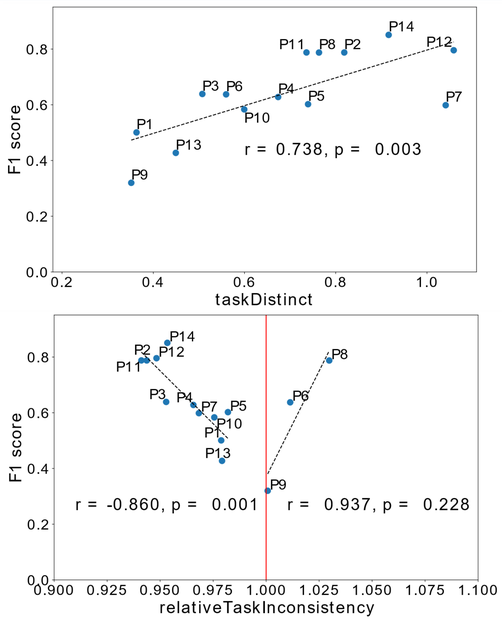
Results

Relationship to classifier performance

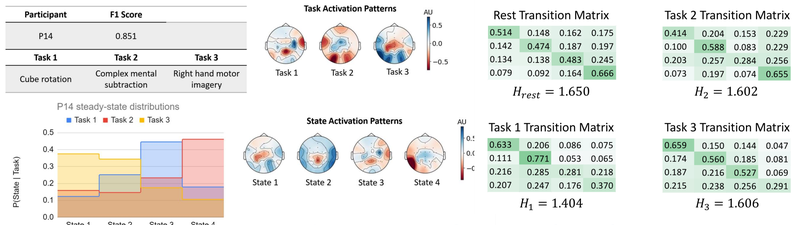
- Positive correlation (N=14) between *taskDistinct* and classifier performance
- Negative correlation observed between F1 scores and participants (N=11) with *relativeTaskInconsistency* < 1
- Metric values for P6, P8, & P9 indicated possible positive relationship between the metric and classifier performance when *relativeTaskInconsistency* > 1



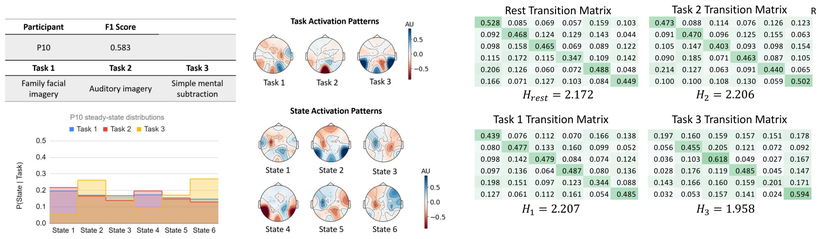
Participant profiles

- Further insight provided by participant profiles
- State distributions (left) show extent to which pattern states are task specific or produced for multiple tasks
- Transition probabilities (right) indicate temporal dynamics of pattern evolution and ability to maintain task specific patterns

High performer (P14)



Moderate performer (P10)



Conclusions and Future Directions

- User assessment approach and metrics yield insights into user performance not afforded by classifier-based metrics
- **Next steps**: Develop training & feedback centred on model & metrics

Acknowledgements

This work has been generously supported by a National Sciences and Engineering Research Council of Canada (NSERC) Canada Graduate Scholarship-Doctoral, a Kimel Family Graduate Student Scholarship in Pediatric Rehabilitation and an Ontario Graduate Scholarship