Sequence Models for By-Trial Decoding of Cognitive Strategies from Neural Data

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Abstract

Understanding trial-by-trial variability in cognitive strategies during decision-making remains a challenge. We combine hidden multivariate pattern (HMP) analysis with a structured state space sequence (S4) model to decode cognitive operations from EEG data. Applied to a speed-accuracy trade-off (SAT) task, HMP identified an additional *Confirmation* operation in accuracy-focused trials, but not in speed-focused trials. Our S4 model predicts the probability of the *Confirmation* operation occurring at the trial level. We use this to show that there are speed trials where the *Confirmation* operation does occur, and accuracy trials where it does not. This operation correlated with higher accuracy and EMG-indexed changes of mind. The introduced method offers a new way to detect and understand cognitive strategies in a data-driven manner.

Keywords: EEG; artificial intelligence; machine learning; sequence modeling; decision-making; speed-accuracy trade-off;

Introduction

Cognitive strategies vary during decision-making, but traditional methods to determine strategies obscure trial-by-trial differences. Common approaches explain behavior through fixed homogeneous processes (Dutilh, Wagenmakers, Visser, & van der Maas, 2011; Ratcliff, Smith, Brown, & McKoon, 2016; Kunkel, Yan, Craigmile, Peruggia, & Van Zandt, 2021). However, neural data suggests heterogeneity in strategy use (van Maanen et al., 2011; van Maanen, Portoles, & Borst, 2021). We propose a novel method based on the theory that the onsets of cognitive operations are embedded in EEG as localized peaks of activity (Borst & Anderson, 2015; Anderson, Zhang, Borst, & Walsh, 2016). We use HMP (Weindel, van Maanen, & Borst, 2024), to estimate condition-level cognitive operations and per-trial probability distributions for the onset of each detected cognitive operation. HMP finds the dominant sequence of cognitive operations per condition, thus disregarding intra-condition variability. We combine HMP with an S4 sequence model architecture which is chosen for its ability to model longer sequences and handle sequential dependencies (Gu, Goel, & Ré, 2022; Gu & Dao, 2024). We train the model to detect the onset of each cognitive operation using EEG data and HMP results as labels. The trained model can be used to detect which cognitive operations were likely to have occurred at trial level, in turn showing the strategy that the participant likely followed.

Applied to a SAT task, where participants had to decide which of two concurrently presented sinusoidal gratings had higher contrast, while focusing on either speed or accuracy, our method reveals an additional operation in the accuracy condition. We use the S4 model's predictions to determine the probability of the additional operation, in both accuracy and speed trials, and link this to behavioral and physiological outcomes.

Methods

Data & Preprocessing

Reanalyzed EEG and EMG data from 20 participants performing a SAT task (Weindel, 2021). EEG was preprocessed (1-50 Hz bandpass, ICA artifact removal).

HMP analysis

Detected cognitive operations per condition using HMP (Weindel et al., 2024) (speed: 3 operations, accuracy: 4 operations). Labeled operations: *Encoding*, *Decision*, *Response* (speed); Additionally *Confirmation* (accuracy).

S4 model

We combine spatial and temporal modeling for EEG sequences (see Figure 1 for a visual overview). First, a $1 \times 1 \times C$ (channels) point-wise convolution extracts global spatial features, followed by temporal dropout for generalization. Temporal relationships are captured via two convolutional layers (scales: 3/9 samples, 12/36 ms), with outputs concatenated. To handle variable trial lengths, we inject a relative positional encoding, emphasizing relative timing over absolute. Features pass through 5 Mamba (Gu & Dao, 2024) layers to integrate spatiotemporal contexts, followed by a classifier. Optimized using Kullback-Leibler divergence.

Results

Condition Differences

HMP revealed an additional *Confirmation* operation in accuracy trials. S4 predicted infrequent *Confirmation* in speed trials (see Figure 2 for a visualization of model performance), where HMP does not.

Behavioral Correlates

Using a generalized linear mixed model analysis revealed that higher z scored average confirmation probability (ACP) predicted correct responses ($OR = 1.13,\ p < 0.01$), but there was an interaction between time pressure condition and ACP value ($OR = 1.27,\ p < 0.001$), indicating that this effect was stronger when speeded responses were required.

EMG Evidence

Speed trials were less likely to contain an additional peak in EMG activity ($OR = 1.34,\ p < 0.001$). However, trials with high ACP showed a higher likelihood of an additional peak in EMG activity ($OR = 1.32,\ p < 0.001$). There was an interaction between time pressure condition and EMG peaks ($OR = 1.36,\ p < 0.001$). An additional peak in EMG activity indicates a confirmation of the outcome of the decision process, possibly leading to a change of mind (Burle, Possamaï, Vidal, Bonnet, & Hasbroucq, 2002).

Discussion

Our method decodes trial-level cognitive strategies from EEG, revealing dynamic *Confirmation* use despite task instructions. This dynamicity emphasizes the need for models capturing

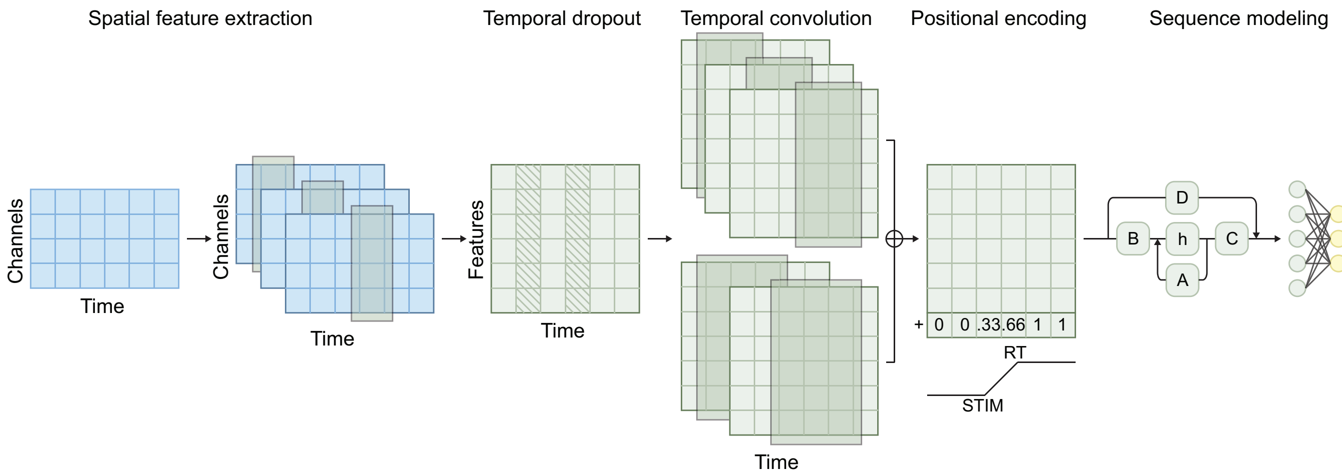

Figure 1: The model architecture used, blue indicates data, green indicates processing, yellow indicates output. Spatial features are extracted from raw data, after which temporal dropout is applied. Temporal convolution is used to model temporal relationships at different time scales. Positional encoding is added to the features, which are fed into a Mamba sequence model.

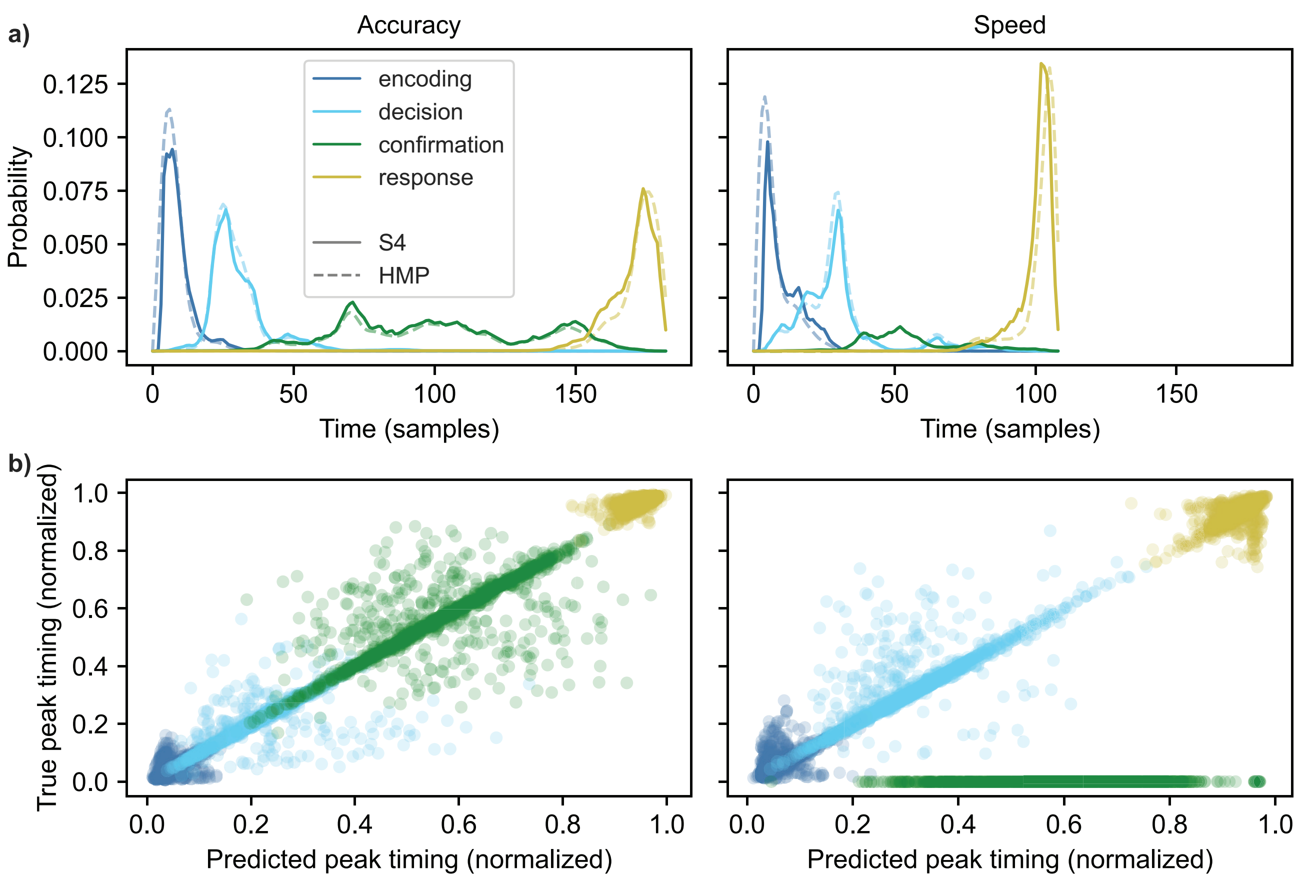

Figure 2: **a)** The model (solid lines) predicts HMP probabilities (dashed line) well at single trial-level. **b)** An aggregate measure of true peak timing (Y-axis) and predicted peak timing (X-axis), values closer to the diagonal indicate a better prediction.

intra-condition variability. Limitations include estimated nature of labels; future work could refine ground truth and devise evaluation metrics for predictions of this nature, as regular metrics are not usable.

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