



Tracking Nonstationarity In Multi-Day Intracortical Neural Recordings During iBCI Cursor Control By A Person With Tetraplegia

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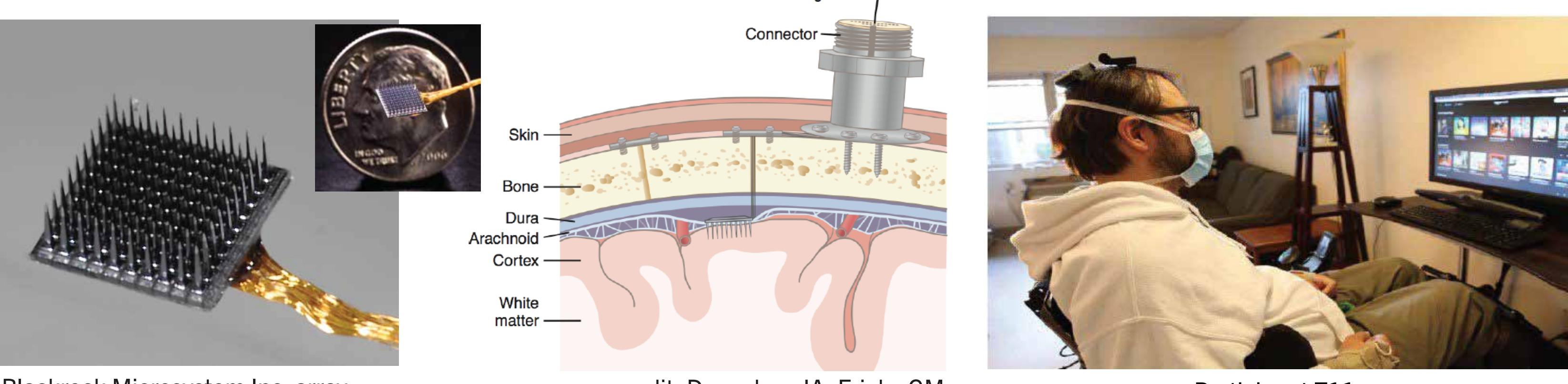
Introduction

- Intracortical brain-computer interfaces (iBCIs) have enabled individuals with tetraplegia to control external devices via decoding movement intentions from neural recordings.
- However, neural activity underlying consistent motor intentions varies over time due to changes in recording conditions, individuals' cognitive states, etc.
- Within- and across-day nonstationarity in the relationship between neural recordings and intended movements can lead to a drop in performance if the decoder is fixed or not robust against such changes (Perge et al, 2013).
- To translate iBCIs for practical everyday use, we propose an approach to track nonstationarity, when a person with tetraplegia controls a computer cursor with a fixed decoder.
- A distance metric is used to monitor the changes in the distribution of neural ensemble activities and decoder outputs, without the knowledge of target location or performance.

Background & Methods

Participants (enrolled in BrainGate2 pilot clinical trial, IDE*)

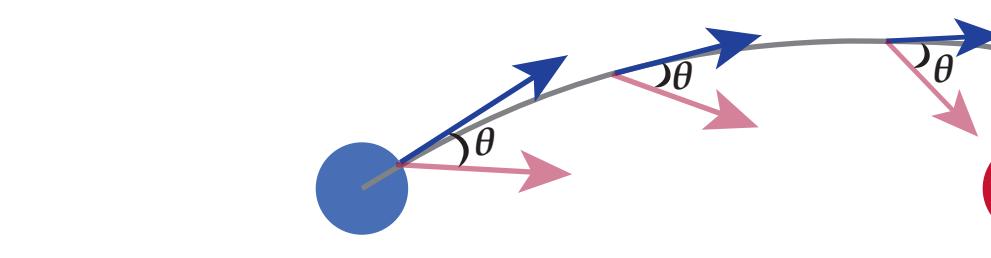
- T11: 37 year-old male with tetraplegia due to C4 AIS-B spinal cord injury
- T5†: 65 year-old male with tetraplegia due to C4 AIS-C spinal cord injury
- Two 96-channel microelectrode arrays implanted both on left precentral gyrus



- Intracortical neural recordings via a wireless broadband iBCI (Simeral et al, 2021)
- Extracted threshold-crossing events and power in the spike band (250 - 5000 Hz)
- BCI cursor task -
 - T11: 5-10 mins closed-loop center-out-and-back task total of 1840 trials over 15 sessions across 142 days (trial day 658-800)
 - T5: 8-16 mins closed-loop random target task; total of 1200 trials over 6 sessions across 28 days (trial day 2121-2149)
- Real-time neural decoders
 - T11: LSTM recurrent neural network (Hosman et al, 2019); Trained and validate on historical data from 20 recent sessions (8441 trials from trial day 576-646); Only include trials with angle error <45°
 - T5: linear regression model Trained on open- & closed-loop random target task on trial day 2121 (decoder day 0)

TABLE I. LSTM TRAINING HYPERPARAMETERS

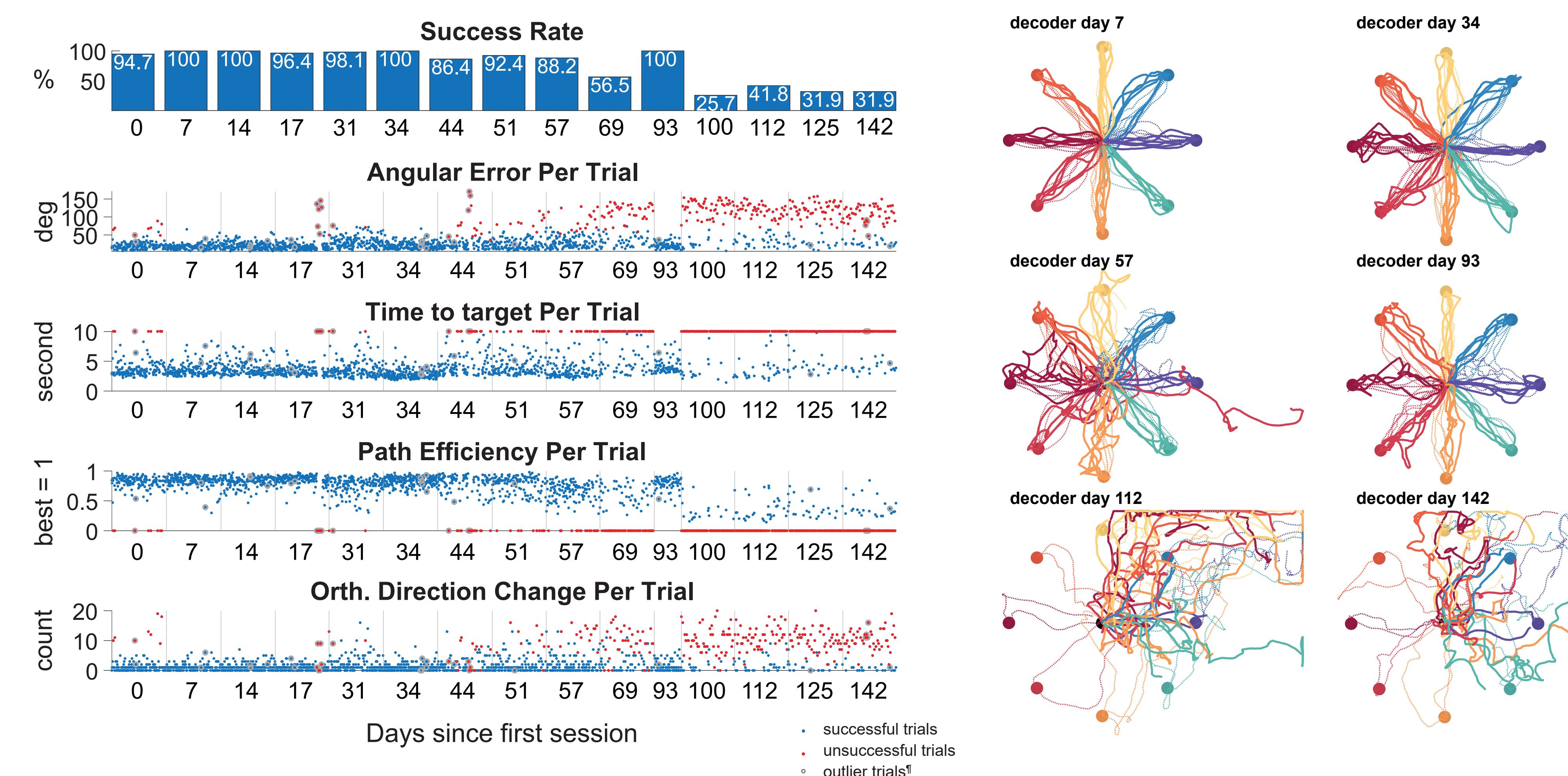
Hidden units	Batch size	Learning rate	Unrolled steps	# Features	Drop out	Loss
100	1024	5e-4	25	384	50%	Mean sq. err



An example of instantaneous angle error (AE) during a trial; (best: 0°, worst: 180°)

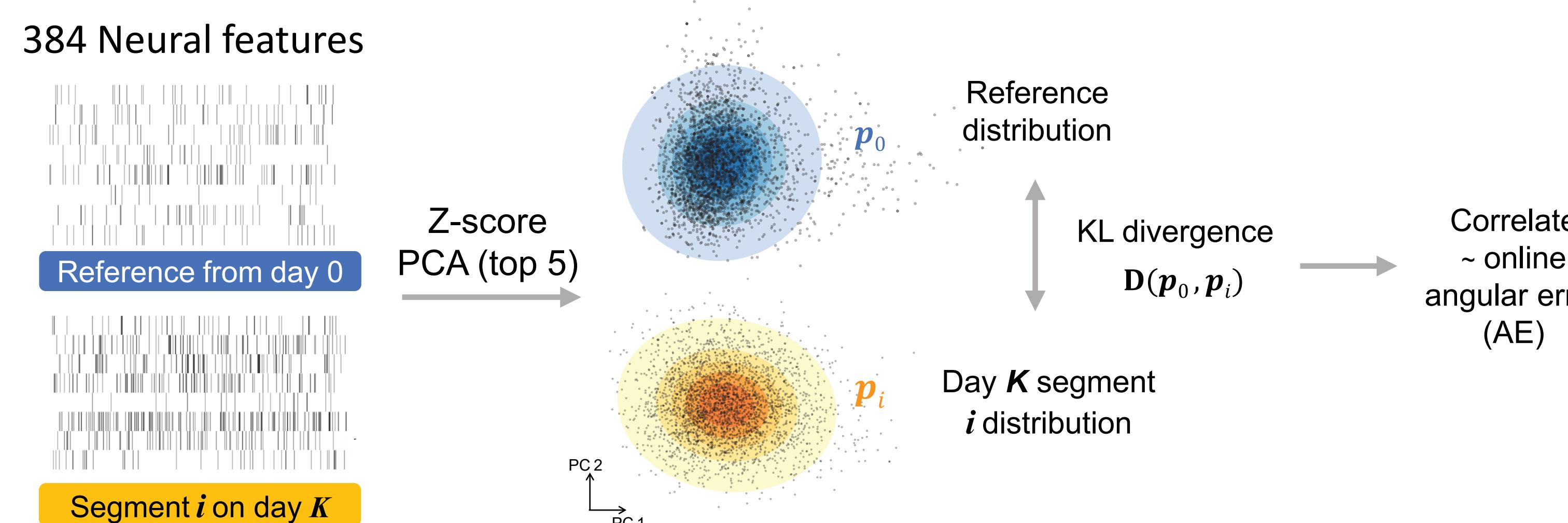
Fixed RNN decoder provides long-term high performance

- T11: 93.8% mean success rate in the first 3 months without any parameter updates, but subsequently degraded to 33.1% in later sessions

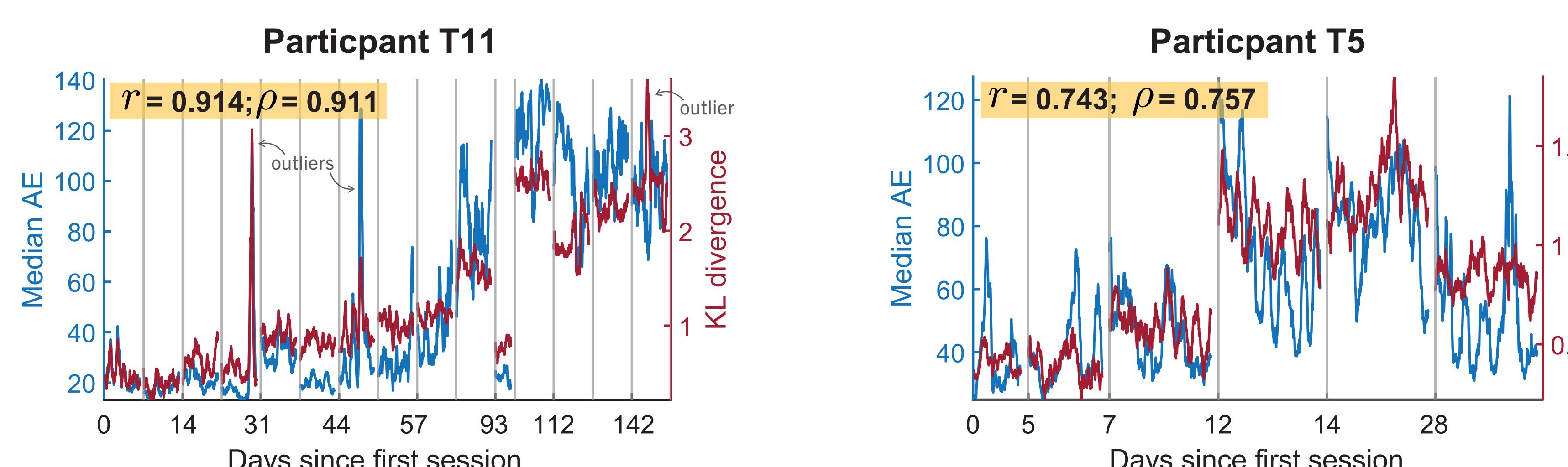


Metric: Quantify nonstationarity by distribution changes

- Compare reference distribution from first day to later days
- Estimate with multivariate Gaussian and report KL divergence between distributions
- Correlate distance metric to online performance across all session days



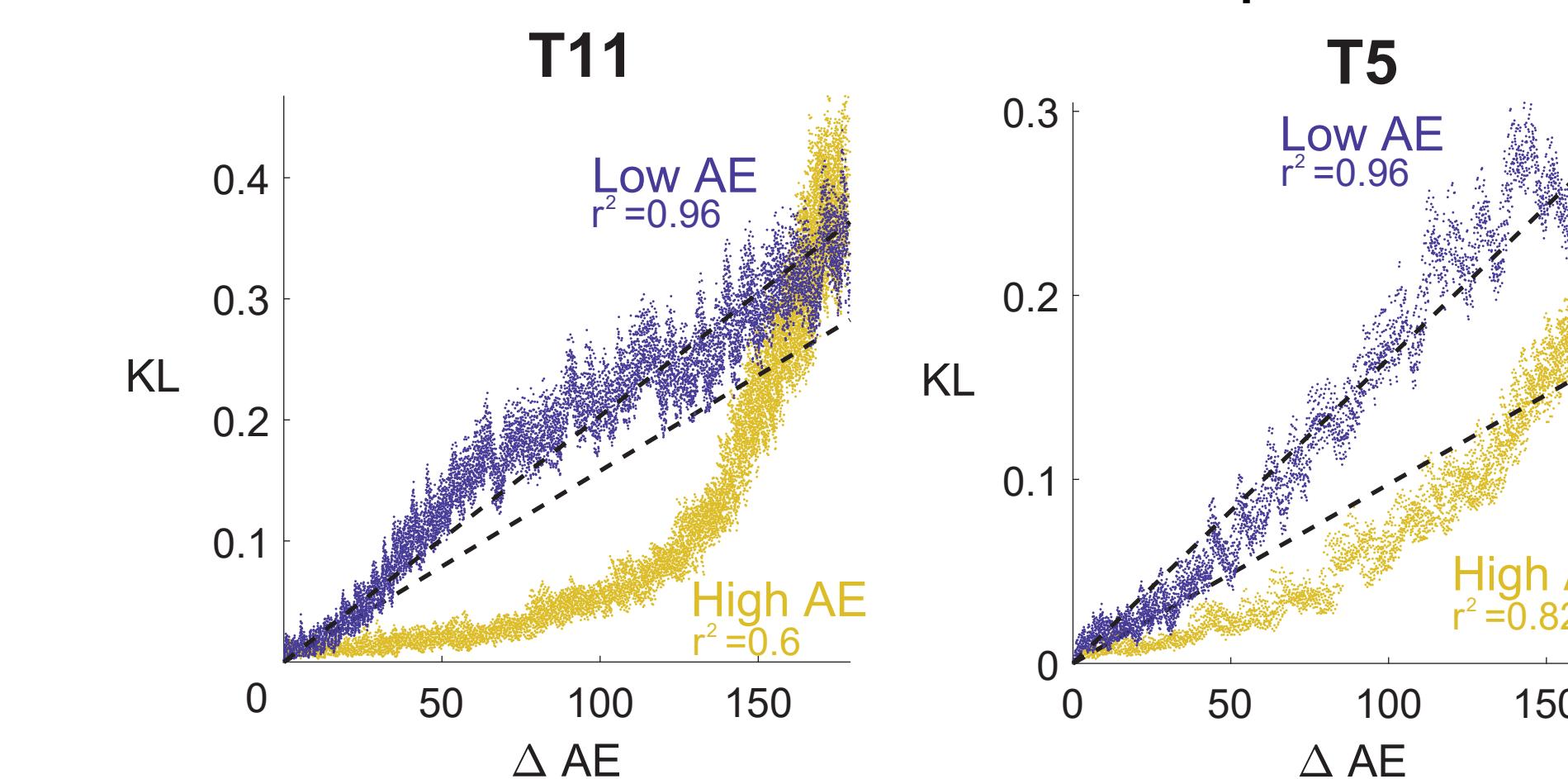
Results: Metric highly correlates with online performance



- Estimated distribution of concatenated neural data and decoder direction output tracks with median angular error with high correlation, regardless of the task structure or target labels
- Can also detect outlier trials where a large amount of recording noise was present (T11)
- Reference day 0 with AE<30°; Update distribution every 2s over a 60-second sliding window
- r - Pearson's correlation coefficient (for linear relationship)
- ρ - Spearman's rank correlation coefficient (for monotonic relationship)

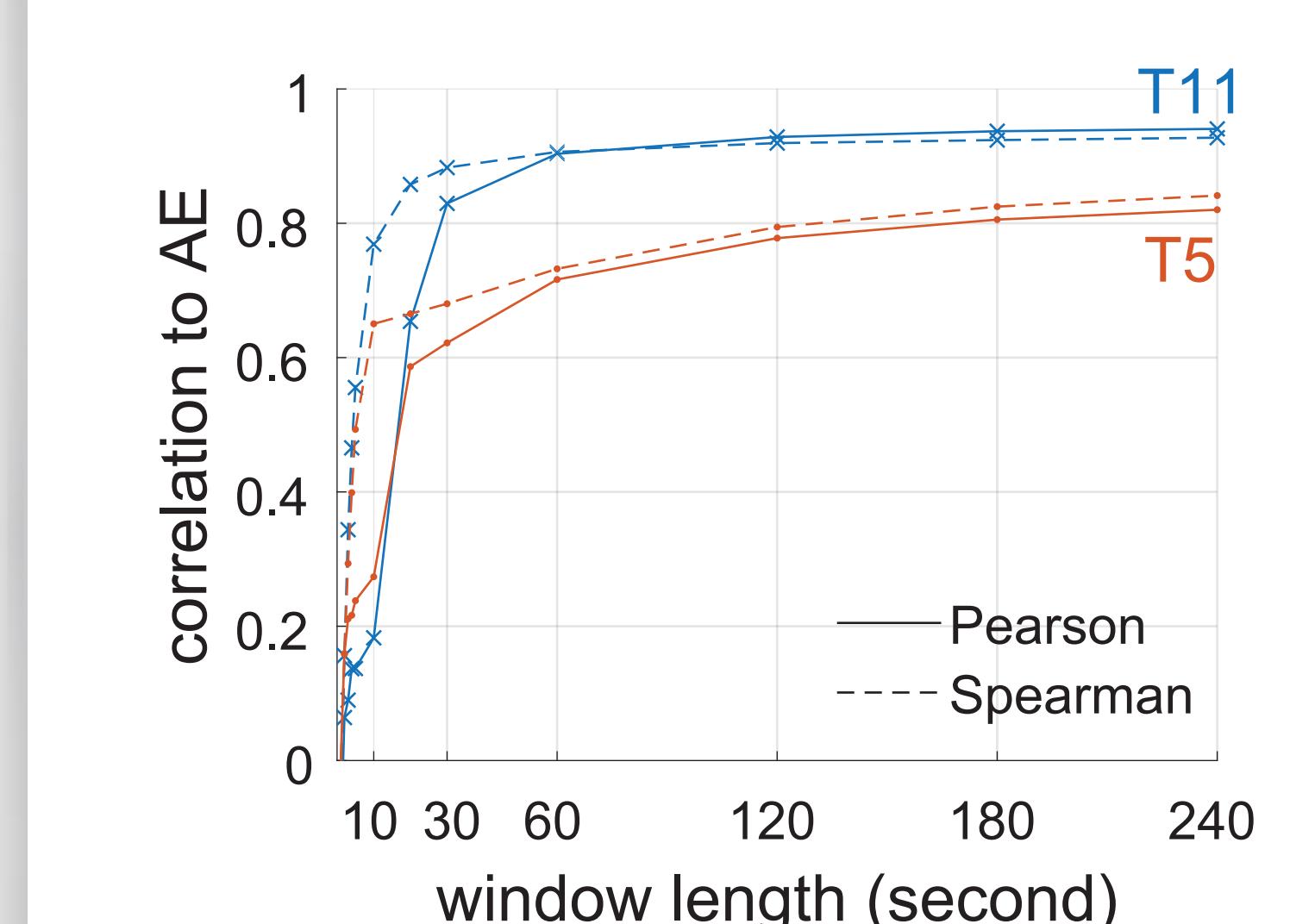
Results: Similarity in neural data reflects angle error

- Decoder performs well when neural patterns at testing are similar to neural patterns at training, where angular error (AE) is low
- When grouping neural data from low-to-high AE, $KL(p_{low\ AE}, p_\theta)$ linearly regresses to difference in median AE between the two compared distributions

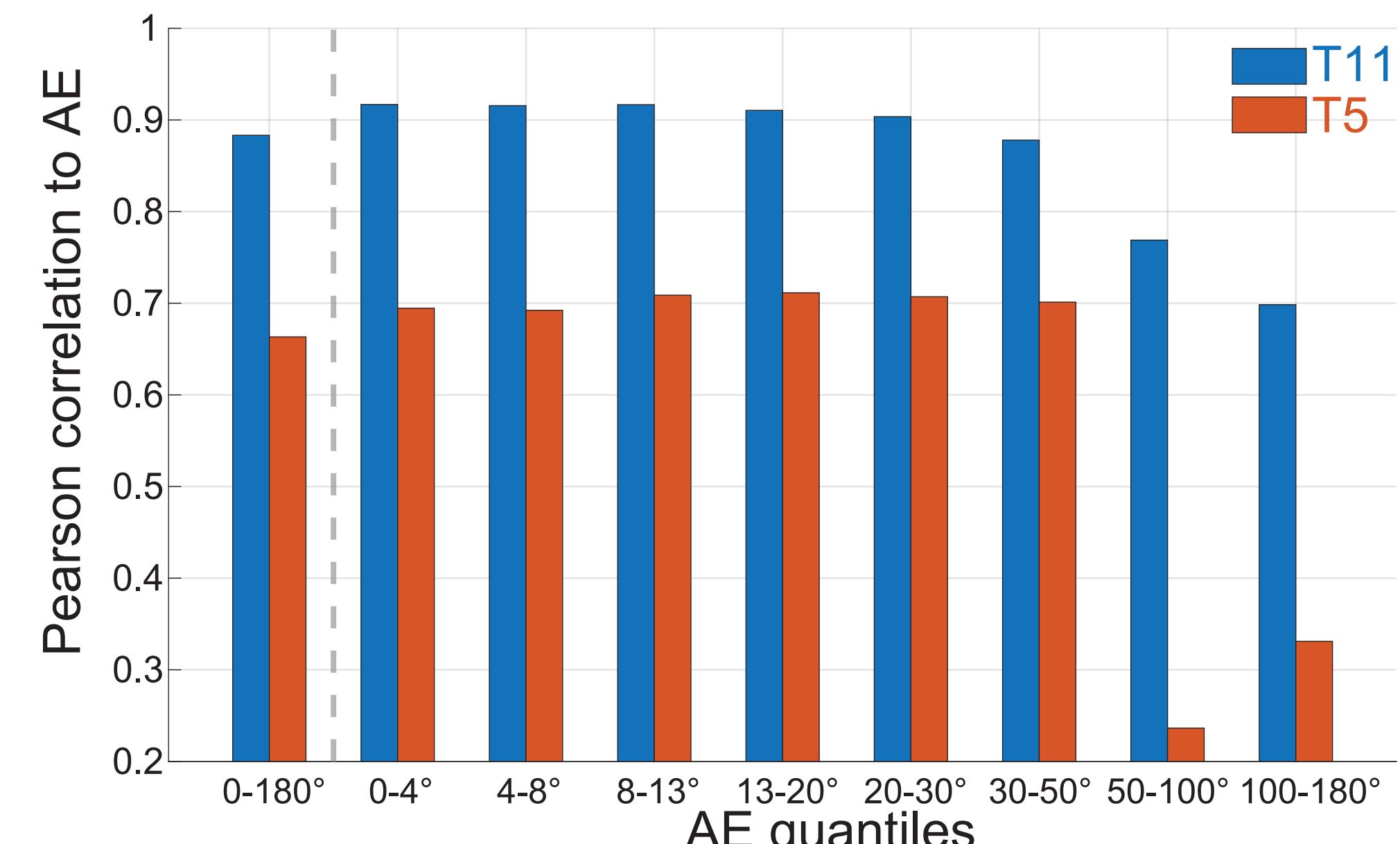


Window Length:

A 60-second window length is sufficient to estimate neural distribution for tracking online performance.

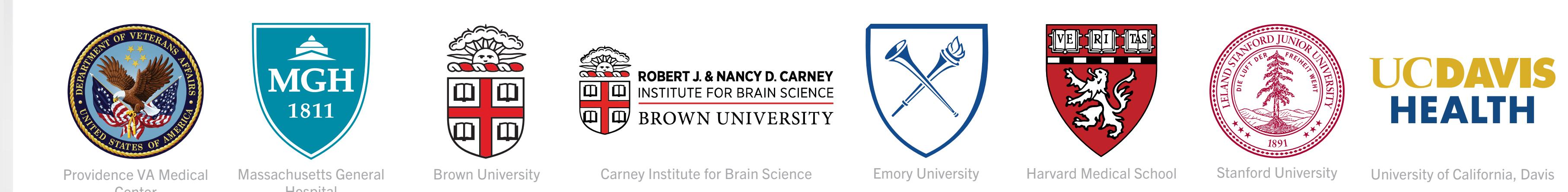


Subselect reference data:
Selecting time steps with low AE from first session as reference data improves correlation.



Conclusions & Future work

- Shifts in neural data relative to epochs of initial good performance can be quantified by KL divergence.
- Our metric is highly predictive of decoder performance over a long period without requiring knowledge of target locations.
- Our method might be useful for triggering a user-engaged or background recalibration as the decoder begins to degrade.
- We will implement this method online as a strategy for recalibration.



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* CAUTION: Investigational Device. Limited by Federal Law to Investigational Use.
† T5's data was collected after the submission of the abstract, hence was not included in the abstract.



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