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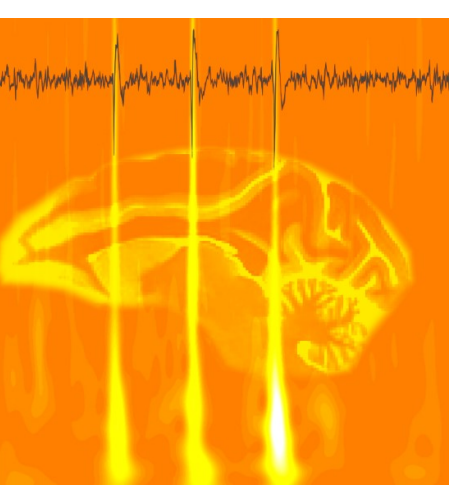
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WHAT IS A BURST? HOW TO SYSTEMATICALLY DETECT SINGLE TRIAL OSCILLATORY DYNAMICS



ZACHARY D LANGFORD, EMMANUEL PROCYK, CHARLES RE WILSON

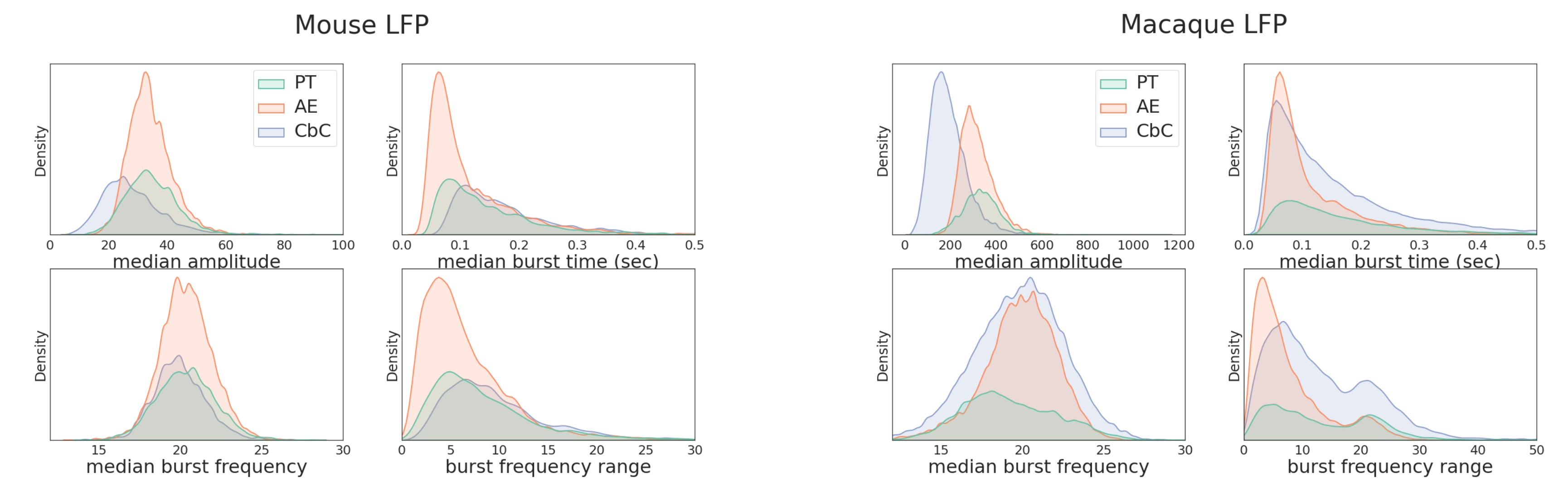
PROBLEM

Motor processes involved in, for example, simple reaction time tasks, are reliably accompanied by trial-averaged differences in the beta band (13-30 Hz), and localized to sensorimotor areas. Yet, this act of averaging appears to do a disservice to the true underlying trial dynamic. It has become increasingly clear that non-sustained transient 'burst-like' rhythms are the predominant feature in the beta band, and also extending into other bands; e.g., gamma band (>30 Hz). While the analysis of the properties of bursts of oscillation in cortex is an increasing feature of the field, the methods used to detect and identify those bursts shows significant variation, and as such the definition of what constitutes a burst must vary as well.

CONTRIBUTION

We characterise burst recovery rates in simulated data and provide evidence that the current method of thresholding TF maps is problematic. Even in high SNR scenarios it is prone to non-detection of bursts, and detecting false bursts. The amplitude-envelope method and the cycle-by-cycle method are prone to difficulties in the model fitting procedures, but tend to recover bursts more reliably, while not giving rise to false detections. Along with the simulation, we applied these methods to recovered burst properties in real electrophysiological signals to detail the differences in burst characteristics.

ELECTROPHYSIOLOGICAL SIGNALS

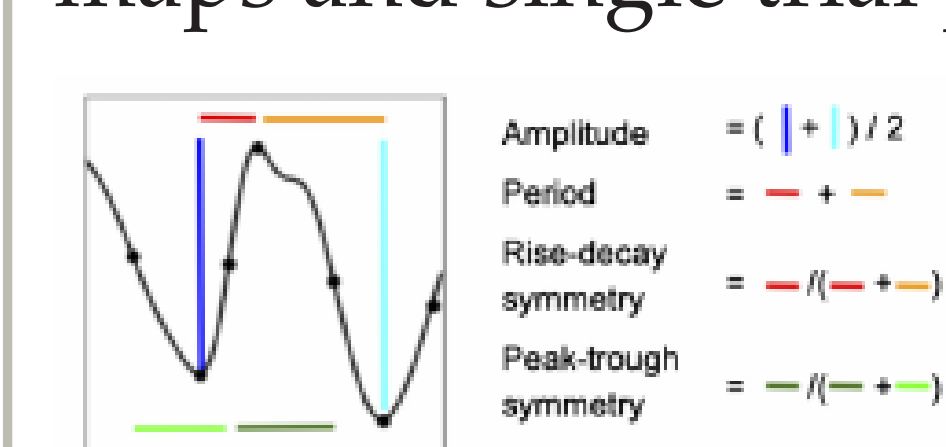
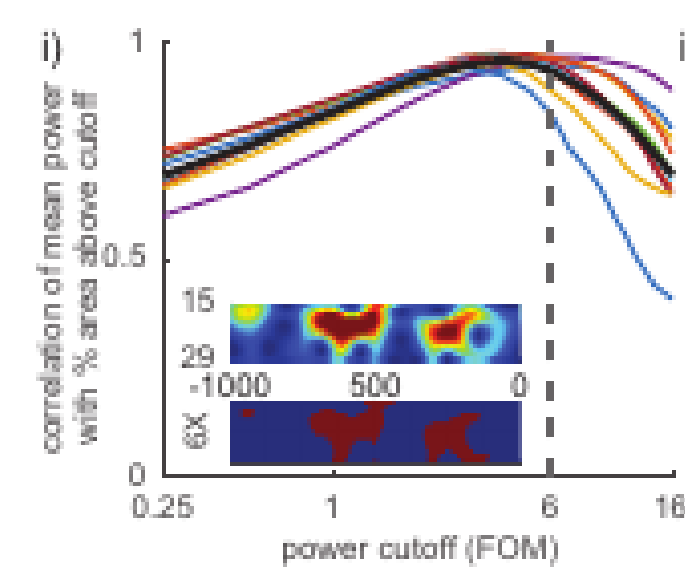


1 second of mouse LFP featured in [1](left); Macaque LFP from our lab 1 second before a response in a problem solving task (right). In both cases we see that PT does not detect as many bursts, and that there are possibly hidden lower amplitude bursts that are being detected by CnC (and arguably AE).

DETECTION METHODS

PT:Power Threshold[1]

The most prominent method to date focuses on finding the highest correlation between the area above in median-thresholded time frequency maps and single trial power.

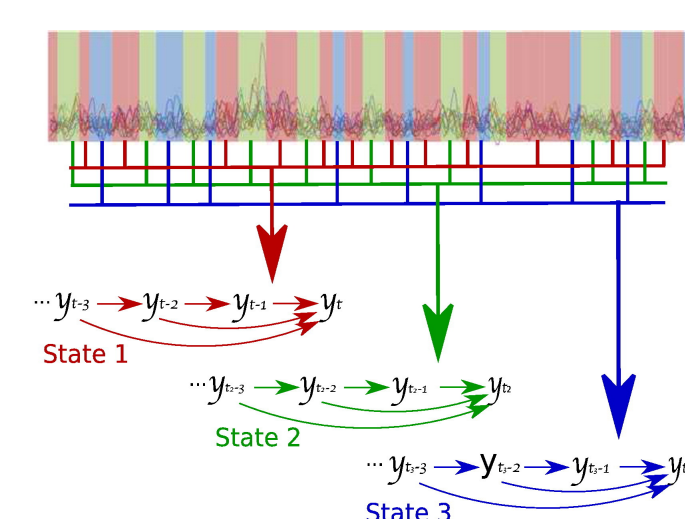


CbC:Cycle-by-cycle[2]

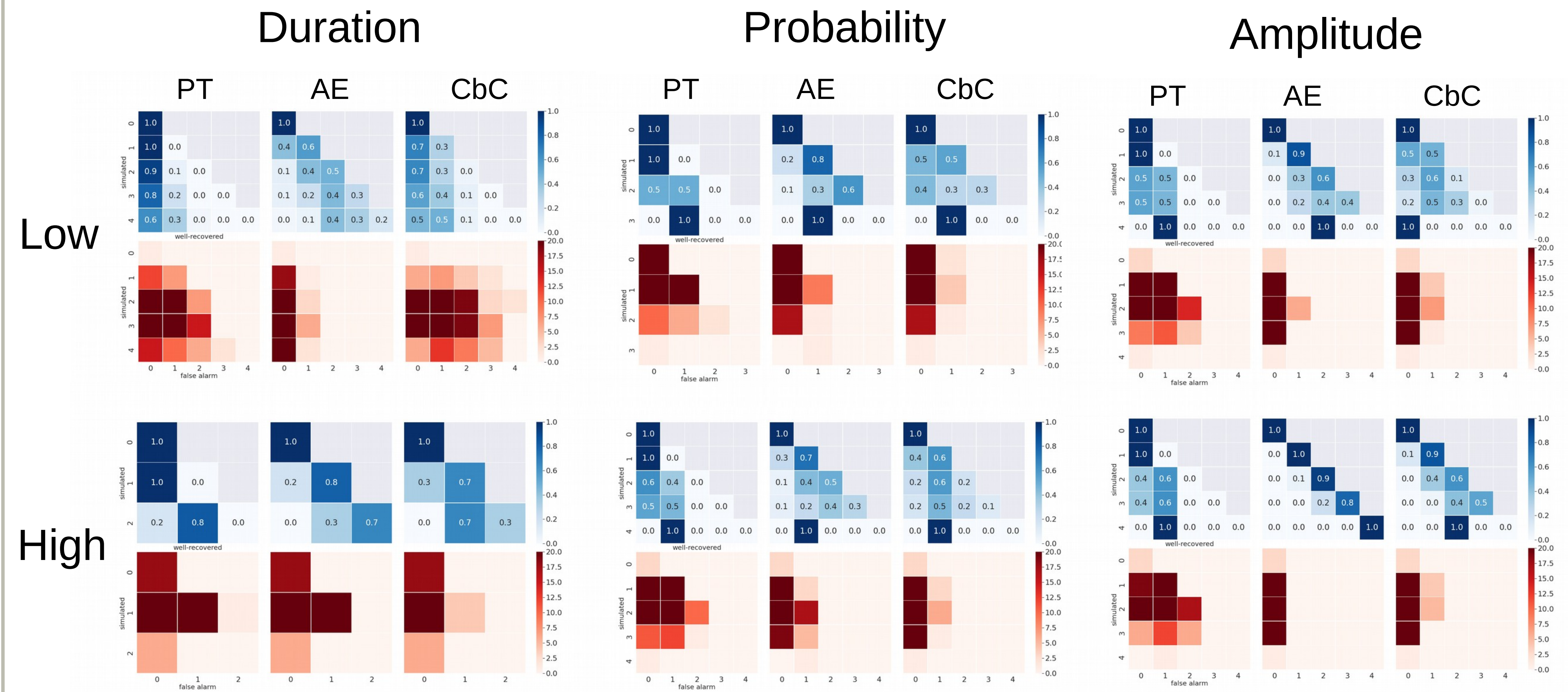
This method focuses on finding regularity in cycles, and is not inherently interested in bursts of high amplitude. In our instantiation we do an exhaustive search of the parameters to find the highest correlation between burst durations per trial and single trial power - similar to the power threshold method.

AE:Amplitude envelope Hidden Markov Model[3]

This approach models the signal using a discrete set of sequential states. Each state is defined by its own set of spectral properties. There is no thresholding, but is complicated due to model fitting. There is a possibility to extend to more complex models.

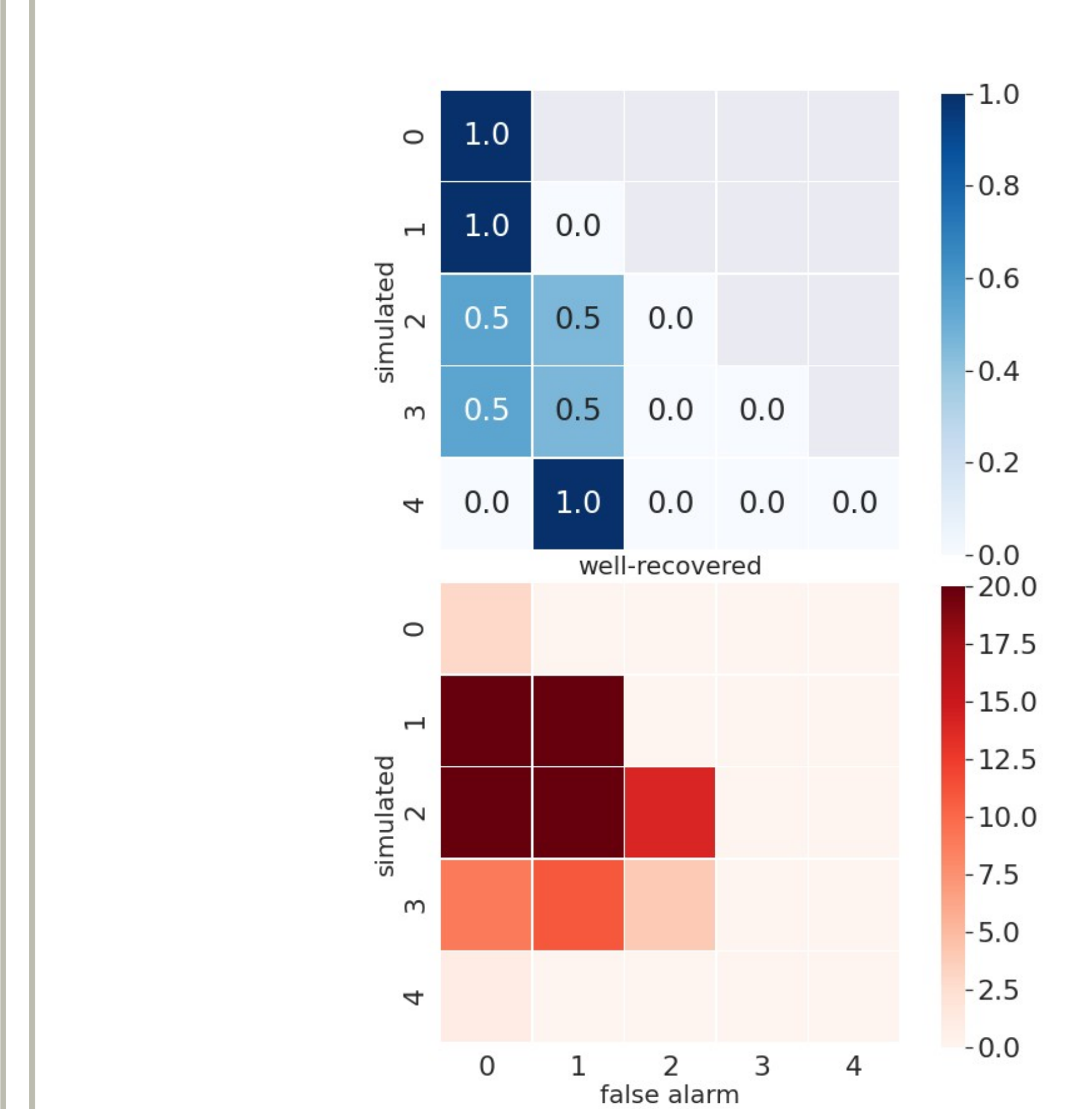


SIMULATED SIGNALS



For a burst to be well-recovered it needed to share greater than 25% of its time points with an actual burst. In general, PT does not recover bursts well, and produces many false alarms - even in a high SNR scenario. AE recovers things relatively well, and in most circumstances does not produce many false alarms. CbC is somewhere in between the two on both counts.

HOW TO INTERPRET PLOTS



TOP: simulated count by recovered count. Higher values closer to diagonal are better, meaning more recovered, less missed. BOTTOM: simulated count by false alarm count. Values on x-axis at 0 are better. In this instance there are lots of misses, and a fair amount of false alarms.

A FUTURE DIRECTION

Based on the simulation we have found that the PT method to detect beta bursts has problems with missing bursts, and incorrectly detecting bursts when they are absent. Both the CbC and AE approaches fair better in both counts - clearly outperforming the PT method. In the real data, we see that a) both the CbC approach and the AE approach pick up many more burst than the PT method, and b) the CbC method picks up lower amplitude bursts and shorter. Going forward we need to better understand the role that lower power bursts of oscillation play in cognitive processes.

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- [1] H. Shin, et. al., The rate of transient beta frequency events predicts behavior across tasks and species. In *elife* 2017
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- [3] D. Viduarre, et. al., Spectrally resolved fast transient brain states in electrophysiological data. In *Neuroimage* 2016