pairwise interactions on Sicalri's Neural Correlates of Dreaming

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Abstract

Here I run pyPSI on two electrodes from Siclari's neural correlates of dreaming paper to see which SPIs perform well for classifying DE vs. NE.

Keywords: information-theory, dreaming, consciousness

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Summary

- I first ran all the SPIs for one subject which took an extremely long time to compute. I then removed those SPIs that are computationally expensive (see this commit) and the computation time came down to around a minute for each recording. The removed SPIs were from Information Theory and Spectral connectivity categories. In the end 187 SPIs were left, out of which only 124 had memory requirements that my computer could satisfy and the rest resulted in out-of-memory errors and NaNs Table 1.

- Managed to get the SPIs requiring octave and java to compute as well.

- I plotted the channels using the `HydroCelGSN256v10.sfp` file into a 3D space and chose once Oz (15) and one Pz (137) channel (see `siclari.ipynb`)

- pySPI is using a quite old version of python (3.9 from 2020) along with a bunch of other libraries whose versions are out of date. This can get quite annoying if you would want to combine pySPI with other packages in the same environment. Nevertheless, I have managed to package everything up and make it work in a reproducible manner using uv.

- Even though some of the SPIs may be undirected, for the sake of simplicity, I only took the upper trianglular entry of the 2x2 matrix to use as a feature for classification.

- The classification is based on the experiment 1 of the original paper Siclari et al. (2017). I wanted to see which SPIs can predict Dreaming Experience (DE) vs No Experience (NE) better.

Results

Similar to the original paper but with less permutation and splits, I do five random 70/30 splits and check for statistical significance using a permutation testing method see. This involves fitting 50 null models (by randomly shuffling the labels) and testing them with cross-validation.

Then, I compare the observed classification performance for each SPI with the combined null distribution of all SPIs. This gives me p-values, which I adjust for multiple comparisons by controlling the family-wise error rate at 0.05 using the Bonferroni method Siclari et al. (2017).

The class balance seemed okay between the two condition. Nevertheless the logistic regression model (glm binomial) should help with that as well.

Based on this method, none of the SPIs were significant as see in Figure 1. The top performing SPIs are presented in table Table 2.

Siclari, F., Baird, B., Perogamvros, L., Bernardi, G., LaRocque, J. J., Riedner, B., Boly, M., Postle, B. R., & Tononi, G. (2017). The neural correlates of dreaming. *Nature Neuroscience*, *20*(6), 872–878. https://doi.org/10.1038/nn.4545

Table 1

SPI stats

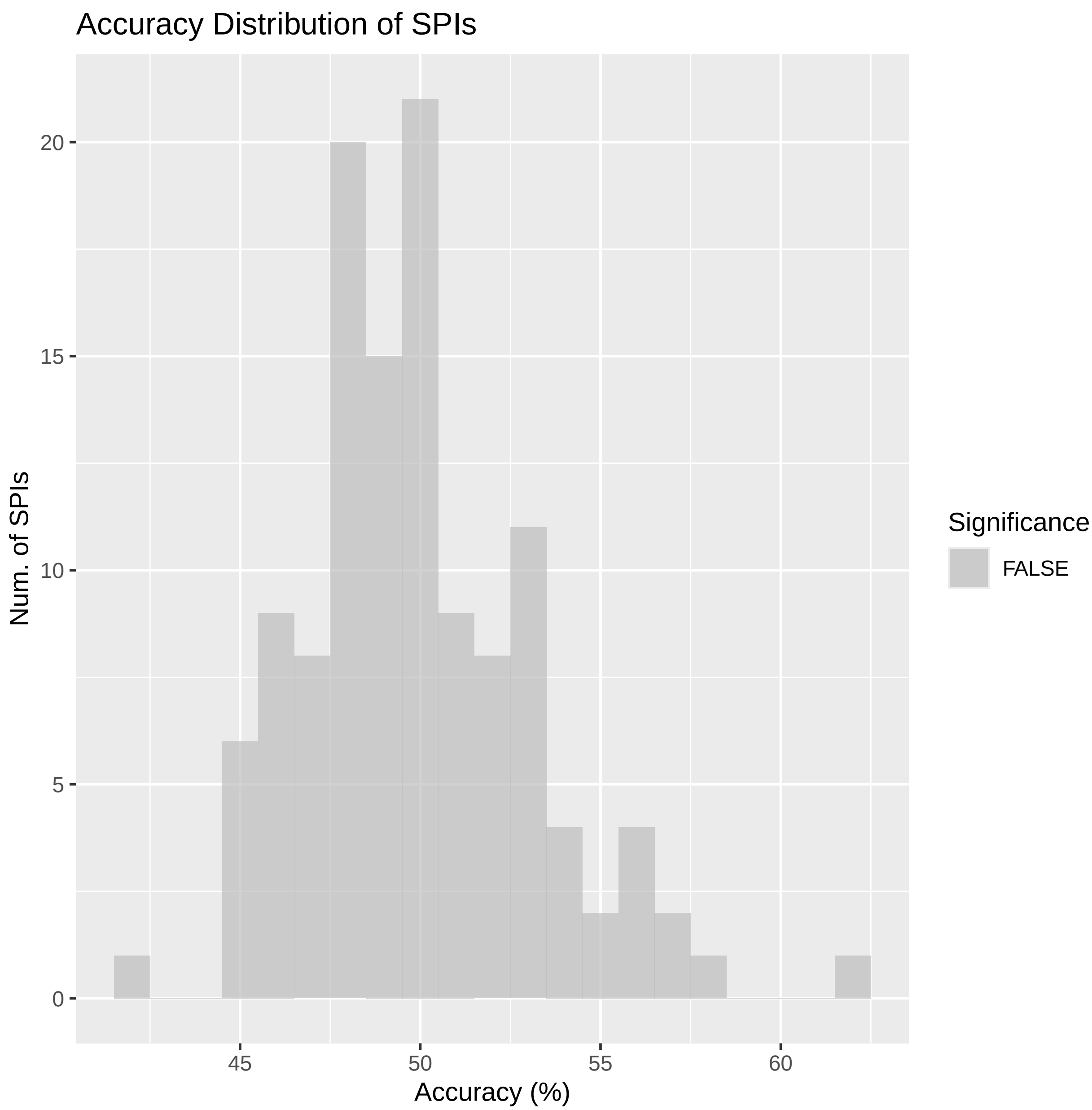
Category	Count
Successful	124
NaNs	55
Constants	8

Table 2

Top 10 Names

	SPI	Accuracy
119	coint_johansen_trace_stat_order.1_ardiff.1	0.6227526
1	cov_EmpiricalCovariance	0.5829730
116	coint_johansen_max_eig_stat_order.1_ardiff.10	0.5685107
115	coint_johansen_trace_stat_order.0_ardiff.1	0.5676933
118	coint_johansen_max_eig_stat_order.1_ardiff.1	0.5627404
113	coint_johansen_trace_stat_order.0_ardiff.10	0.5624172
112	coint_johansen_max_eig_stat_order.0_ardiff.10	0.5570116
76	psi_multitaper_mean_fs.1_fmin.0_fmax.0.25	0.5561177
59	phase_multitaper_mean_fs.1_fmin.0.25_fmax.0.5	0.5538754
57	phase_multitaper_mean_fs.1_fmin.0_fmax.0.5	0.5520878

Figure 1


Accuracy Distribution of SPIs
Num. of SPIs
0
5
10
15
20
45
50
55
60
Accuracy (%)
Significance
FALSE