5. TDE-HMM Analysis (8 states)

Jupyter notebook with a single run of a **TDE-HMM analysis** for the SDMT dataset using the OSL Dynamics Toolbox from the Oxford Centre for Human Brain Activity (OHBA) Ananalysis Group.

Reference: Gohil C., Huang R., Roberts E., van Es M.W.J., Quinn A.J., Vidaurre D., Woolrich M.W. (2023) osl-dynamics: A toolbox for modelling fast dynamic brain activity. eLife 12:RP91949 https://doi.org/10.7554/eLife.91949.2

Required input files/folders to run this Notebook:

- **DIR_parceled_raw**: folder with all fully processed .fif files (from Notebook 1. Preprocessing MEG Python) --> Needed in order to extract event timestamps
- **input_path**: The .fif files that are used as input for the TDE-HMM data preparation. These files are renamed + had all STIM channels removed.
- **subjectinfo.mat**: file with all clinical patient information
- **all_epochs_paths**: folder containg all MNE epoch objects where the stimulus onset is seen as the DIODE signal
- **mask_file**: "MNI152_T1_8mm_brain_nii.gz" is the brain mask used to plot the spatial power
- **Parcels_38_names.txt**: .txt file with the names of the 38 parcels of the parcellation file
- **parcellation file**: "fmri_d100_parcellation_with_PCC_reduced_2mm_ss5mm_ds8mm.nii.gz" **with 38 parcels** needs to be 4D (3 dimensions for spatial coordinates and 1 for each parcel) with sform_code = 1

Import statements

In [1]:
```
## work in a virtual environment with pre-installed osl_dynamics

# import useful libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
import seaborn as sns
from scipy.io import loadmat
import tensorflow
import glob
import mne
import pickle
import os

import glmtools as glm
import glmtools.design as glm_

# import osl dynamics functions
import osl_dynamics
from osl_dynamics.data import Data
from osl_dynamics.models.hmm import Config
```

```
from osl_dynamics.models.hmm import Model
from osl_dynamics import simulation
from osl_dynamics.utils import plotting
from osl_dynamics.models import load
from osl_dynamics.inference import modes
from osl_dynamics.data import task
from osl_dynamics.analysis import spectral
from osl_dynamics.analysis import power
from osl_dynamics.analysis import connectivity
from osl_dynamics.analysis import statistics
```

```
/home/olivierb/.local/lib/python3.9/site-packages/tqdm/auto.py:21: TqdmWa
rning: IProgress not found. Please update jupyter and ipywidgets. See htt
ps://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

Input variables !

In [2]:
```
remove_STIM_chans = False
model_training = True      # False if you have already trained a model, and
n_states = 8
model_name = "Dynamic_Models/HMM_TDE_ALL_8states_25epochs"
```

Load in data for all subjects - **Orthogonalized & Sign-Flipped**

In [3]:
```
DIR_parceled_raw = "/home/olivierb/FULLY_PROCESSED/processed_WITH_orth_WITH_
all_parceled_raw = sorted(glob.glob(DIR_parceled_raw + '*.fif'))

wanted_sub_IDs = [subject[-12:-8] for subject in all_parceled_raw]
```

Remove subjects that should be excluded

In [4]:
```
## Subjects indices to remove
# The subjects excluded in the post-processing analyses relate to prior finc
# As well as additional findings throughout this Thesis (Olivier Burta, 2024
# - missing DIODE channel (in the event extraction step)
# - missing BUTTON press response channels
# - flat PSD-spectrum
subjects_to_exclude = [0, 5, 38, 41, 49, 62, 68, 83, 84, 106, 107, 114, 119,
                       30]
all_data = []

# List of file-paths for remaining subjects
for idx in range(len(all_parceled_raw)):
    if idx not in subjects_to_exclude:
        all_data.append(all_parceled_raw[idx])

# List of subjects IDs for remaining subjects
subject_IDs_group_analysis = []
for idx in range(len(wanted_sub_IDs)):
    if idx not in subjects_to_exclude:
        subject_IDs_group_analysis.append(wanted_sub_IDs[idx])

print(len(subject_IDs_group_analysis))
```

```
110
```

Remove STIM channels and save all files in ./Input_files_HMM/final/

Only **run once** for a **new dataset**

Why are we doing this? Because all input files need to only contain the signal channels

In [5]:
```
if remove_STIM_chans:

    for i in range(len(all_data)):

        raw = mne.io.read_raw_fif(all_data[i], verbose=False)
        code = all_data[i][-12:-8]

        # Identify stimulus channels
        stim_channels = [ch for ch in raw.ch_names if ch.startswith('STI')]

        # Exclude stimulus channels
        raw_without_stim = raw.copy().drop_channels(stim_channels)

        # Save the modified raw data (without STIM channels)
        raw_without_stim.save('/home/olivierb/Input_files_HMM/final/sub_' +
```

Data as input to HMM: input_path variable

In [6]:
```
input_path = "/home/olivierb/Input_files_HMM/final/"
input_data_HMM = sorted(glob.glob(input_path + 'sub_*_raw.fif'))
print(len(input_data_HMM))
```

```
110
```

TDE data preparation

Convert input data using Data() function

In [7]:
```
from osl_dynamics.data import Data

training_data = Data(input_data_HMM)    # all subjects!
```

```
Loading files: 100%|██████████| 110/110 [01:56<00:00,  1.06s/it]
```

Data preparation before HMM inference

In [8]:
```
methods = {
    "tde_pca": {"n_embeddings": 15, "n_pca_components": 80},
    "standardize": {},

}
training_data.prepare(methods)
```

```
Calculating PCA components: 100%|██████████| 110/110 [01:22<00:00,  1.33it/
s]
2024-05-05 14:58:28 INFO osl-dynamics [base.py:650:tde_pca]: Explained vari
ance: 57.1%
TDE-PCA: 100%|██████████| 110/110 [01:04<00:00,  1.69it/s]
Standardize: 100%|██████████| 110/110 [00:12<00:00,  9.12it/s]
```

Out[8]:
```
<osl_dynamics.data.base.Data at 0x7fd370743730>
```

Config object

The **important hyperparameters** to specify are:

- **n_states**, the number of states. must be pre-specified. We advise starting with something **between 6-14**.
- **sequence_length and batch_size**. Determines the amount of bathces and window length for model parameter updates during training.
- **learn_means and learn_covariances**. Typically, if we train on **AE data** we set learn_means and learn_covariances to **True**, whereas if you're training on **TDE/PCA data**, then we only learn the covariances, i.e. we set **learn_means=False**.
- **learning_rate**. On large datasets, we find a lower learning rate leads to a lower final loss. We recommend a value **between 1e-2 and 1e-4**.
- **n_epochs**, the number of epochs. This is the number of times you loop through the data.

In [14]:

```
from osl_dynamics.models.hmm import Config

# Create a config object
config = Config(
    n_states=n_states,
    n_channels=training_data.n_channels,
    sequence_length=2000,
    learn_means=False,
    learn_covariances=True,
    batch_size=64,
    learning_rate=5e-4,
    n_epochs=200,
)
```

Building/Initialising/Training the model

In [15]:

```
%%time
from osl_dynamics.models.hmm import Model
from osl_dynamics.models import load

## Only do all of this if a model needs to be trained
if model_training:
    # Build a Model class and print a summary
    model = Model(config)
    model.summary()

    # Initialise the training --> Helpfulf to start the full training with a
    init_history = model.random_state_time_course_initialization(training_da

    # Train the model
    history = model.fit(training_data)

    # Save trained model
    model.save(model_name)

## If model exists already, load it instead
```

```
else:
    model = load(model_name)
```

```
Model: "HMM"
__________________________________________________________________________
_________________________
 Layer (type)                Output Shape         Param #     Connecte
d to
==========================================================================
=========================
 inputs (InputLayer)         [(None, 2000, 88)]   0           []

 tf.split_2 (TFOpLambda)     [(None, 2000, 80),   0           ['inputs
[0][0]']
                              (None, 2000, 8)]

 static_loss_scaling_factor (St  ()               0           ['tf.spl
it_2[0][0]']
 aticLossScalingFactorLayer)

 means (VectorsLayer)        (8, 80)              640         ['tf.spl
it_2[0][0]',
                                                               'static
_loss_scaling_factor[0][0
                                                              ]']

 covs (CovarianceMatricesLayer)  (8, 80, 80)      25920       ['tf.spl
it_2[0][0]',
                                                               'static
_loss_scaling_factor[0][0
                                                              ]']

 ll_loss (CategoricalLogLikelih  (1,)             0           ['tf.spl
it_2[0][0]',
 oodLossLayer)                                                 'means
[0][0]',
                                                               'covs
[0][0]',
                                                               'tf.spl
it_2[0][1]']

==========================================================================
=========================
Total params: 26,560
Trainable params: 25,920
Non-trainable params: 640
__________________________________________________________________________
_________________________
```

```
2024-05-05 18:51:42 INFO osl-dynamics [hmm.py:422:random_state_time_cours
e_initialization]: Random state time course initialization
2024-05-05 18:51:44 INFO osl-dynamics [hmm.py:435:random_state_time_cours
e_initialization]: Using 153 out of 153 batches
2024-05-05 18:51:44 INFO osl-dynamics [hmm.py:440:random_state_time_cours
e_initialization]: Initialization 0
2024-05-05 18:51:47 INFO osl-dynamics [hmm.py:1013:set_random_state_time_
course_initialization]: Setting random means and covariances
```

```
Epoch 1/1
153/153 [==============================] - 1487s 9s/step - rho: 0.2853 -
lr: 0.0050 - loss: 218661.4405
```

```
2024-05-05 19:17:59 INFO osl-dynamics [hmm.py:440:random_state_time_cours
e_initialization]: Initialization 1
2024-05-05 19:18:01 INFO osl-dynamics [hmm.py:1013:set_random_state_time_
course_initialization]: Setting random means and covariances
```

```
Epoch 1/1
153/153 [==============================] - 1493s 9s/step - rho: 0.2853 - lr: 0.0050 - loss: 218762.1629
```

```
2024-05-05 19:44:21 INFO osl-dynamics [hmm.py:440:random_state_time_course_initialization]: Initialization 2
2024-05-05 19:44:23 INFO osl-dynamics [hmm.py:1013:set_random_state_time_course_initialization]: Setting random means and covariances
```

```
Epoch 1/1
153/153 [==============================] - 1527s 10s/step - rho: 0.2853 - lr: 0.0050 - loss: 218690.0907
```

```
2024-05-05 20:11:16 INFO osl-dynamics [hmm.py:463:random_state_time_course_initialization]: Using initialization 0
```

```
Epoch 1/25
153/153 [==============================] - 1511s 10s/step - rho: 0.2853 -
lr: 0.0050 - loss: 201401.6668
Epoch 2/25
153/153 [==============================] - 1493s 9s/step - rho: 0.1995 -
lr: 0.0045 - loss: 190650.1733
Epoch 3/25
153/153 [==============================] - 1467s 9s/step - rho: 0.1577 -
lr: 0.0041 - loss: 185839.5632
Epoch 4/25
153/153 [==============================] - 1455s 9s/step - rho: 0.1322 -
lr: 0.0037 - loss: 183646.6767
Epoch 5/25
153/153 [==============================] - 1450s 9s/step - rho: 0.1149 -
lr: 0.0034 - loss: 181541.2846
Epoch 6/25
153/153 [==============================] - 1448s 9s/step - rho: 0.1022 -
lr: 0.0030 - loss: 179894.8749
Epoch 7/25
153/153 [==============================] - 1410s 9s/step - rho: 0.0925 -
lr: 0.0027 - loss: 178842.8936
Epoch 8/25
153/153 [==============================] - 1398s 9s/step - rho: 0.0847 -
lr: 0.0025 - loss: 177616.1826
Epoch 9/25
153/153 [==============================] - 1442s 9s/step - rho: 0.0784 -
lr: 0.0022 - loss: 176633.9306
Epoch 10/25
153/153 [==============================] - 1458s 9s/step - rho: 0.0731 -
lr: 0.0020 - loss: 175316.7160
Epoch 11/25
153/153 [==============================] - 1317s 8s/step - rho: 0.0686 -
lr: 0.0018 - loss: 174451.8833
Epoch 12/25
153/153 [==============================] - 1292s 8s/step - rho: 0.0647 -
lr: 0.0017 - loss: 173446.6254
Epoch 13/25
153/153 [==============================] - 1296s 8s/step - rho: 0.0613 -
lr: 0.0015 - loss: 172581.5198
Epoch 14/25
153/153 [==============================] - 1302s 8s/step - rho: 0.0583 -
lr: 0.0014 - loss: 171424.7739
Epoch 15/25
153/153 [==============================] - 1296s 8s/step - rho: 0.0556 -
lr: 0.0012 - loss: 170657.9873
Epoch 16/25
153/153 [==============================] - 1356s 9s/step - rho: 0.0532 -
lr: 0.0011 - loss: 169990.1434
Epoch 17/25
153/153 [==============================] - 1304s 8s/step - rho: 0.0511 -
lr: 0.0010 - loss: 169424.7220
Epoch 18/25
153/153 [==============================] - 1290s 8s/step - rho: 0.0492 -
lr: 9.1342e-04 - loss: 168865.0733
Epoch 19/25
153/153 [==============================] - 1294s 8s/step - rho: 0.0474 -
lr: 8.2649e-04 - loss: 168644.3320
Epoch 20/25
153/153 [==============================] - 1300s 8s/step - rho: 0.0457 -
lr: 7.4784e-04 - loss: 168614.7358
Epoch 21/25
153/153 [==============================] - 1295s 8s/step - rho: 0.0442 -
lr: 6.7668e-04 - loss: 167932.7856
Epoch 22/25
```

```
153/153 [==============================] - 1318s 8s/step - rho: 0.0429 -
lr: 6.1228e-04 - loss: 167432.2471
Epoch 23/25
153/153 [==============================] - 1368s 9s/step - rho: 0.0416 -
lr: 5.5402e-04 - loss: 167529.0861
Epoch 24/25
153/153 [==============================] - 1303s 8s/step - rho: 0.0404 -
lr: 5.0129e-04 - loss: 167137.6305
Epoch 25/25
153/153 [==============================] - 1295s 8s/step - rho: 0.0393 -
lr: 4.5359e-04 - loss: 167012.2085
CPU times: user 4d 4h 17min 54s, sys: 20h 26min 14s, total: 5d 44min 9s
Wall time: 10h 48min 58s
```

Extract **alpha** - alpha contains the raw hidden state time courses across the entire concatenated MEG data

In [16]:
```
alpha = model.get_alpha(training_data)
#alpha = pickle.load(open(model_name + "/data/alpha.pkl","rb"))
```

```
Getting alpha: 100%|██████████| 110/110 [04:09<00:00,  2.27s/it]
```

In [17]:
```
## Save extracted alpha inside the folder path
# Save the python lists as a pickle files -> can be inside the folder of the

os.makedirs(model_name + "/data", exist_ok=True)
pickle.dump(alpha, open(model_name + "/data/alpha.pkl", "wb"))
```

0. Verify alpha timecourse (of FLAT state)

This extra section served to investigate why one of the extracted states showed a flat ERF activation, close to 0 spatial power, and abnormal coherence spectra.

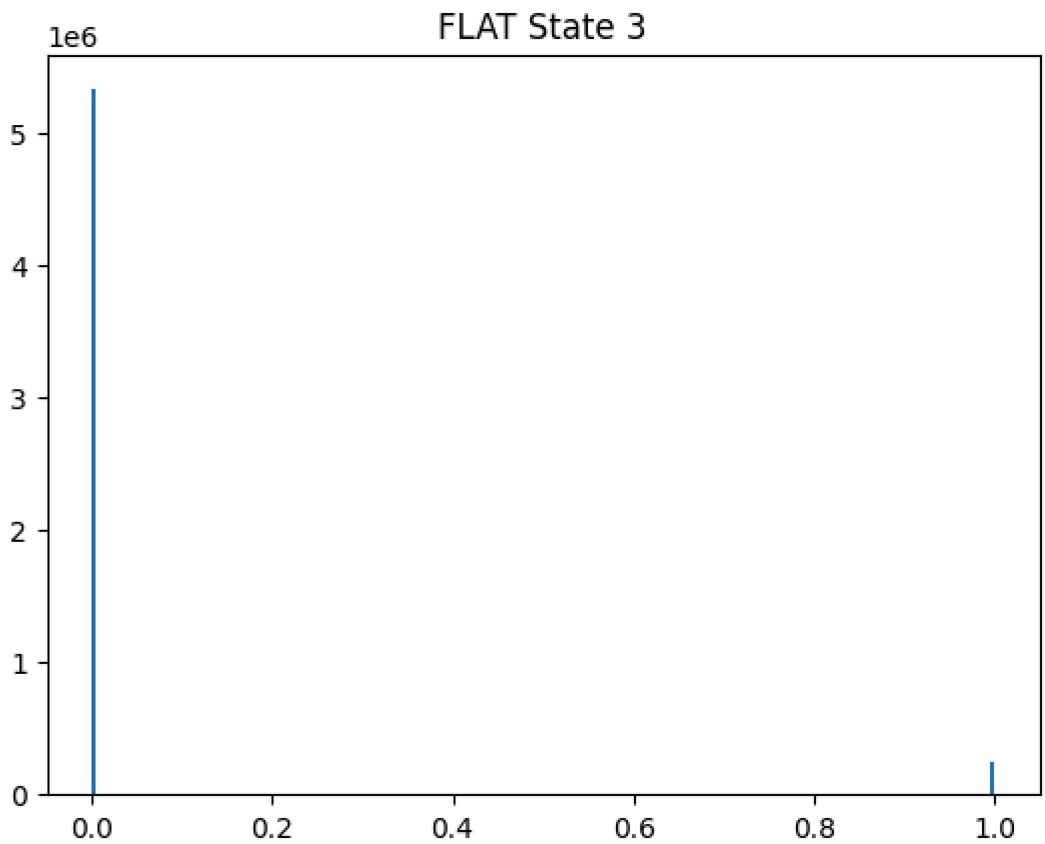
In [ ]:
```
idx_state_flat = 2 # State 3
idx_state_good = 5

fig,ax = plt.subplots(nrows=np.shape(alpha)[0], ncols=2, figsize=(9,4*np.sha

# loop over all subjects
for subject in range(np.shape(alpha)[0]):
    ax[subject,0].plot(alpha[subject][:,idx_state_flat])
    ax[subject,1].plot(alpha[subject][:,idx_state_good])
plt.show()
```

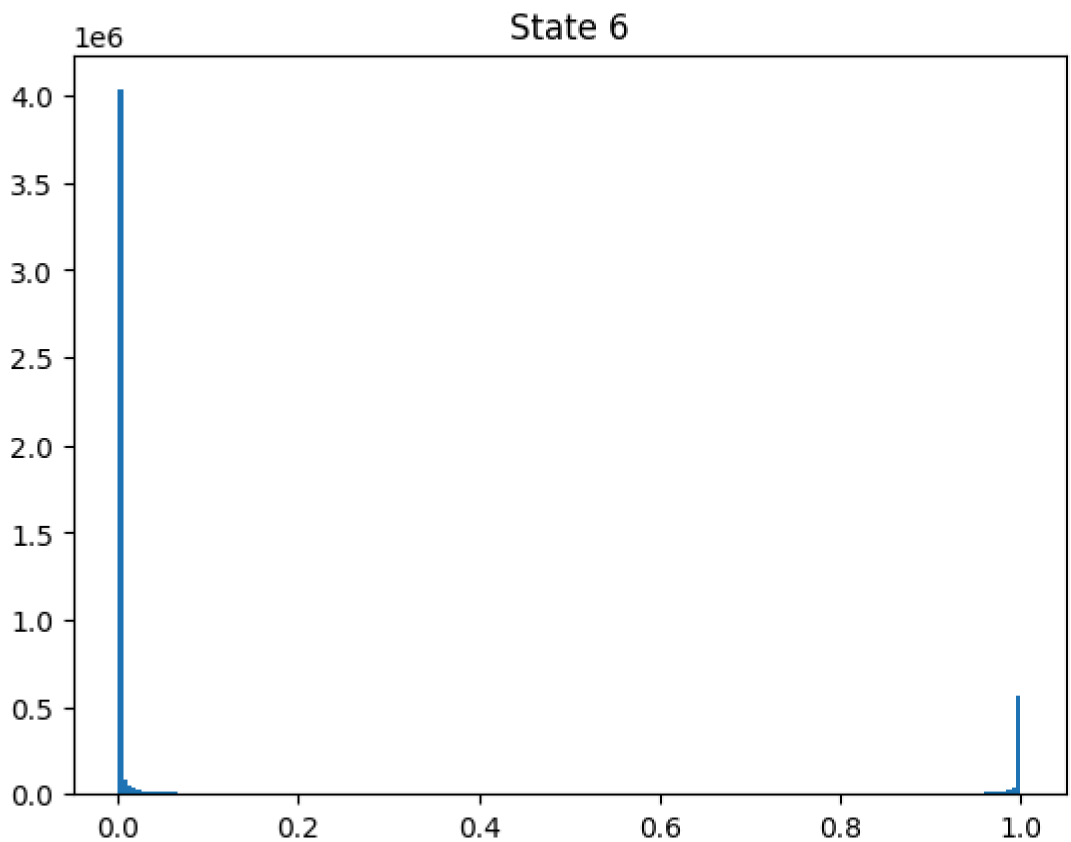
In [16]:
```
all_flat = []
all_good = []

#for subject in range(np.shape(alpha)[0]):
for subject in range(20):
    all_flat.append(alpha[subject][:,idx_state_flat])
    all_good.append(alpha[subject][:,idx_state_good])

out_flat = np.concatenate(all_flat).ravel().tolist()
out_good = np.concatenate(all_good).ravel().tolist()
```

In [17]:
```
plt.hist(out_flat, bins=200)
plt.title('FLAT State 3')
plt.figure()
```

```
plt.hist(out_good, bins=200)
plt.title('State 6')
```

Out[17]: Text(0.5, 1.0, 'State 6')



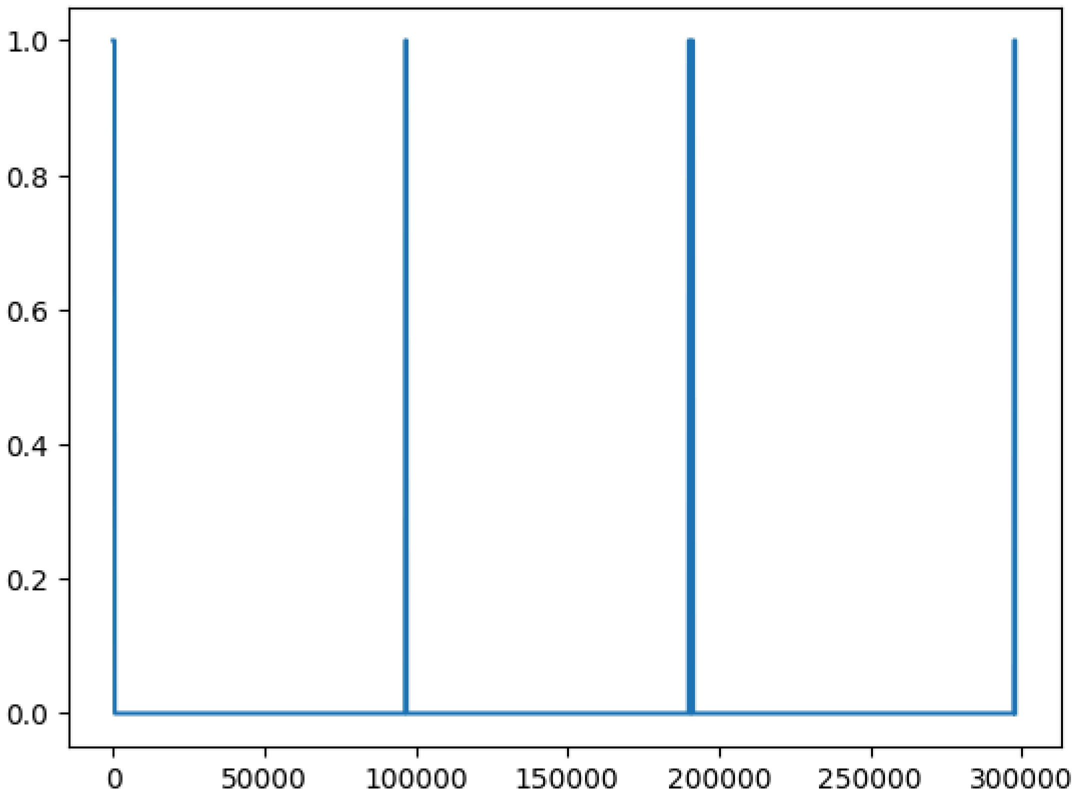


Extract the timepoints where state probability = 1

In [18]:
```
stc = modes.argmax_time_courses(alpha)

stc_single = stc[0][:,idx_state_flat] # 1st subject

print(np.shape(stc_single))

plt.plot(stc_single)
```

```
(298000,)
```

Out[18]:
```
[<matplotlib.lines.Line2D at 0x7fcc1e44cdf0>]
```



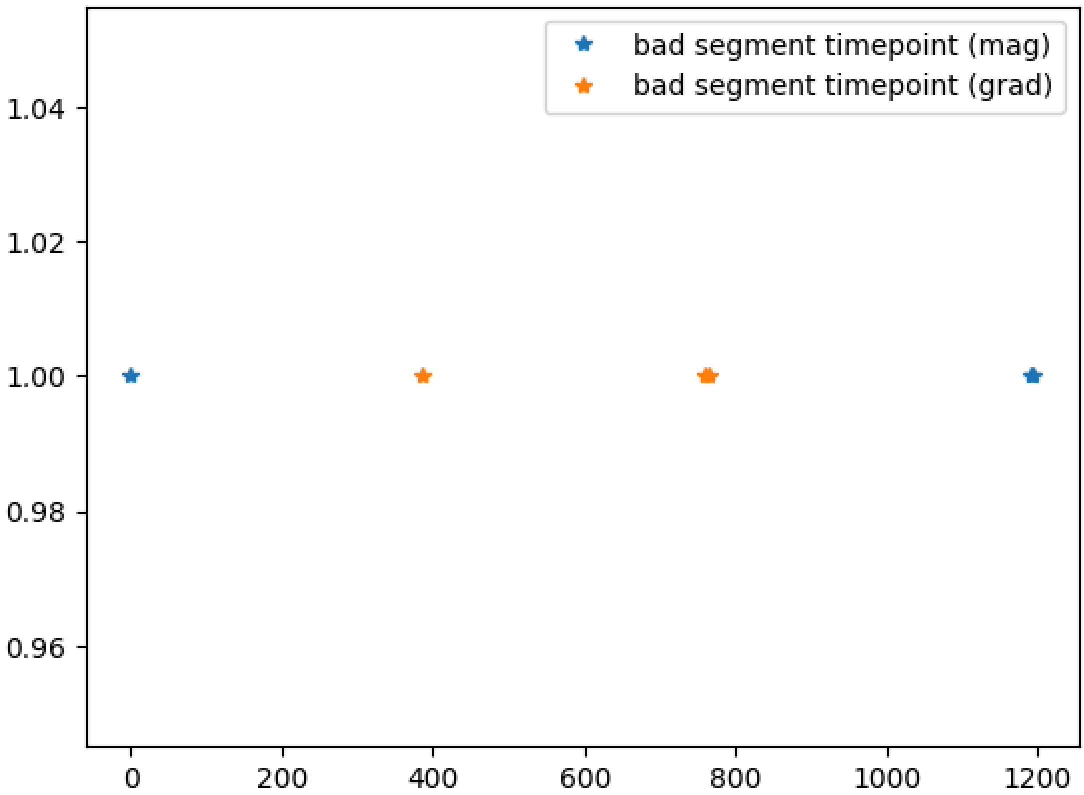
Extract timepoints of annotated bad signal quality

In [44]:
```
loaded = mne.io.read_raw_fif(input_data_HMM[0])
print(loaded.info)

# Get annotations
annotations = loaded.annotations

# Find timepoints with 'bad_segment_mag' or 'bad_segment_grad' annotations
bad_segment_mag_idx = [i for i, description in enumerate(annotations.descrip
bad_segment_grad_idx = [i for i, description in enumerate(annotations.descri

# Get timepoints corresponding to the indices
bad_segment_mag_timepoints = annotations.onset[bad_segment_mag_idx]
bad_segment_grad_timepoints = annotations.onset[bad_segment_grad_idx]

bad_segment_mag_timepoints = [timepoint - loaded.first_samp/250.0 for timepo
bad_segment_grad_timepoints = [timepoint - loaded.first_samp/250.0 for timep

print("Timepoints with 'bad_segment_mag' annotation:", bad_segment_mag_timep
print("Timepoints with 'bad_segment_grad' annotation:", bad_segment_grad_tim

print(len(bad_segment_mag_timepoints))
print(len(bad_segment_grad_timepoints))
```

```
plt.plot(bad_segment_mag_timepoints, np.ones_like(bad_segment_mag_timepoints
plt.plot(bad_segment_grad_timepoints, np.ones_like(bad_segment_grad_timepoir
plt.legend()
```

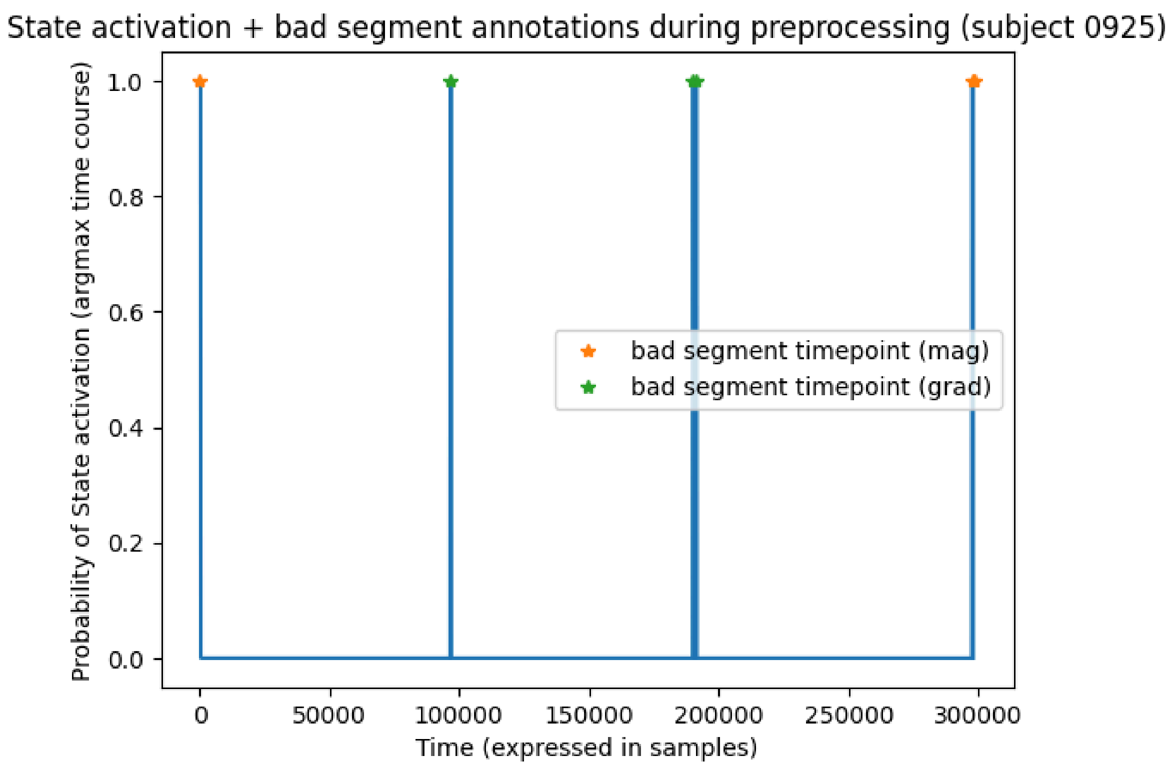
```
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_0925_raw.f
if...
    Range : 26250 ... 325749 =     105.000 ...  1302.996 secs
Ready.
<Info | 11 non-empty values
 bads: []
 ch_names: parcel_0, parcel_1, parcel_2, parcel_3, parcel_4, parcel_5,
...
 chs: 38 misc
 custom_ref_applied: False
 description: Vectorview system OSL BATCH PROCESSING APPLIED ON 06/11/202
3 ...
 dig: 0 items
 file_id: 4 items (dict)
 highpass: 0.0 Hz
 lowpass: 125.0 Hz
 meas_date: 2015-04-21 09:25:17 UTC
 meas_id: 4 items (dict)
 nchan: 38
 projs: []
 sfreq: 250.0 Hz
>
Timepoints with 'bad_segment_mag' annotation: [0.0, 1189.995972, 1193.995
972]
Timepoints with 'bad_segment_grad' annotation: [385.996002, 759.995972, 7
63.995972]
3
3
```

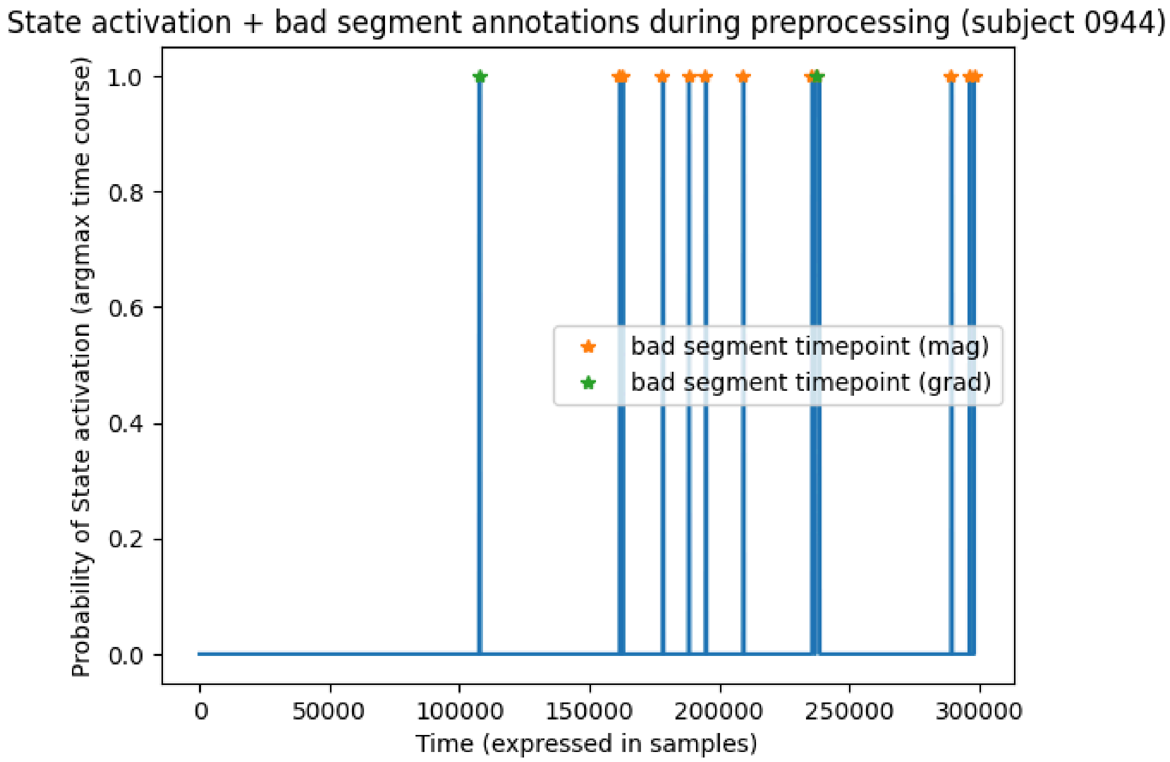
Out[44]: `<matplotlib.legend.Legend at 0x7efbe1e6ed00>`

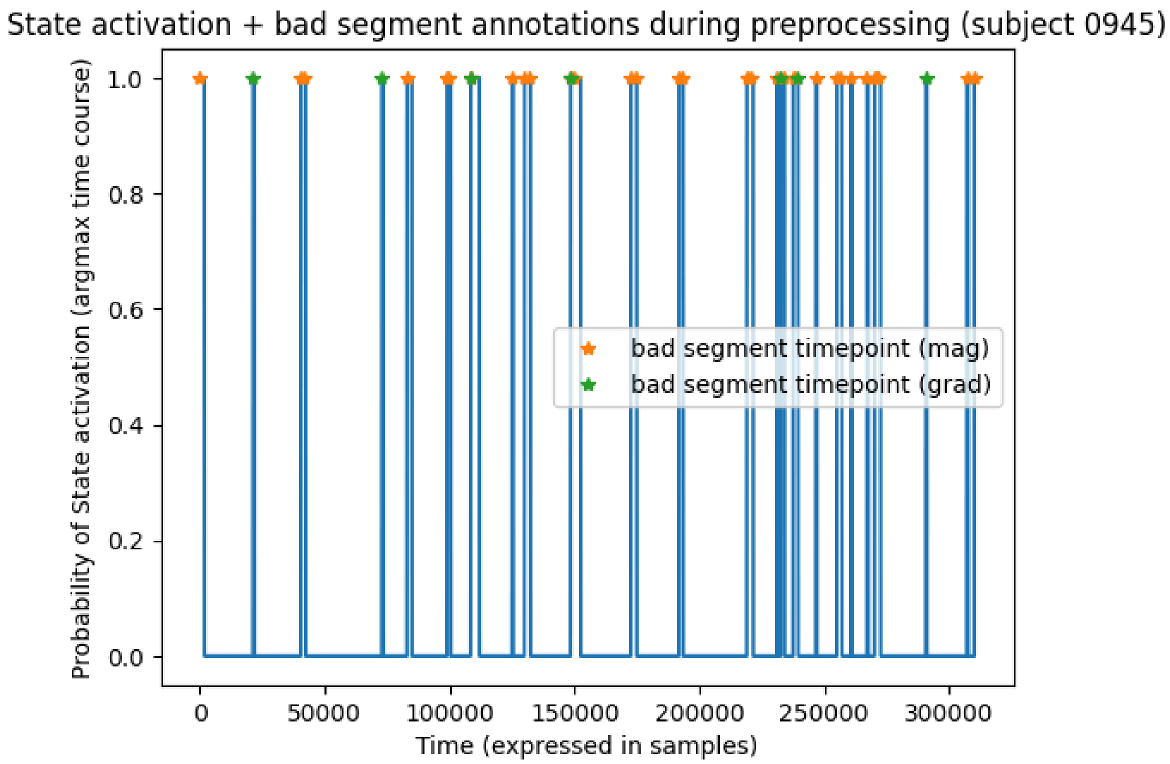


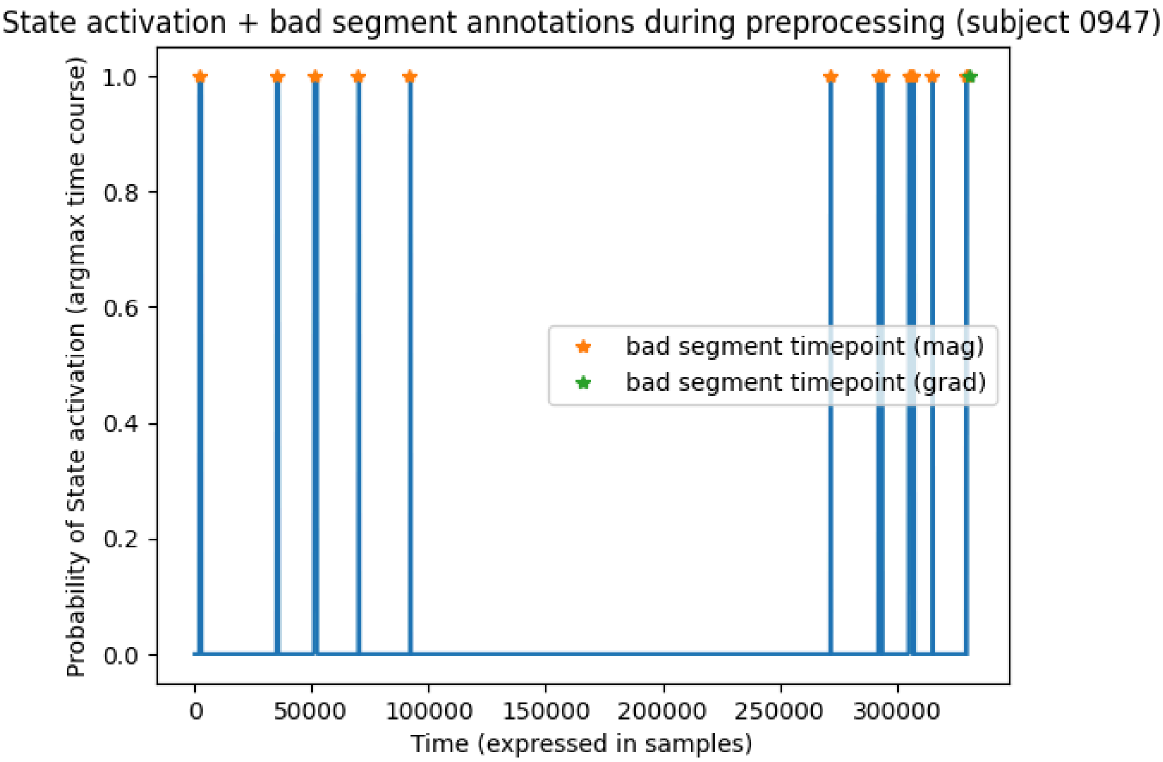
Now for all subjects

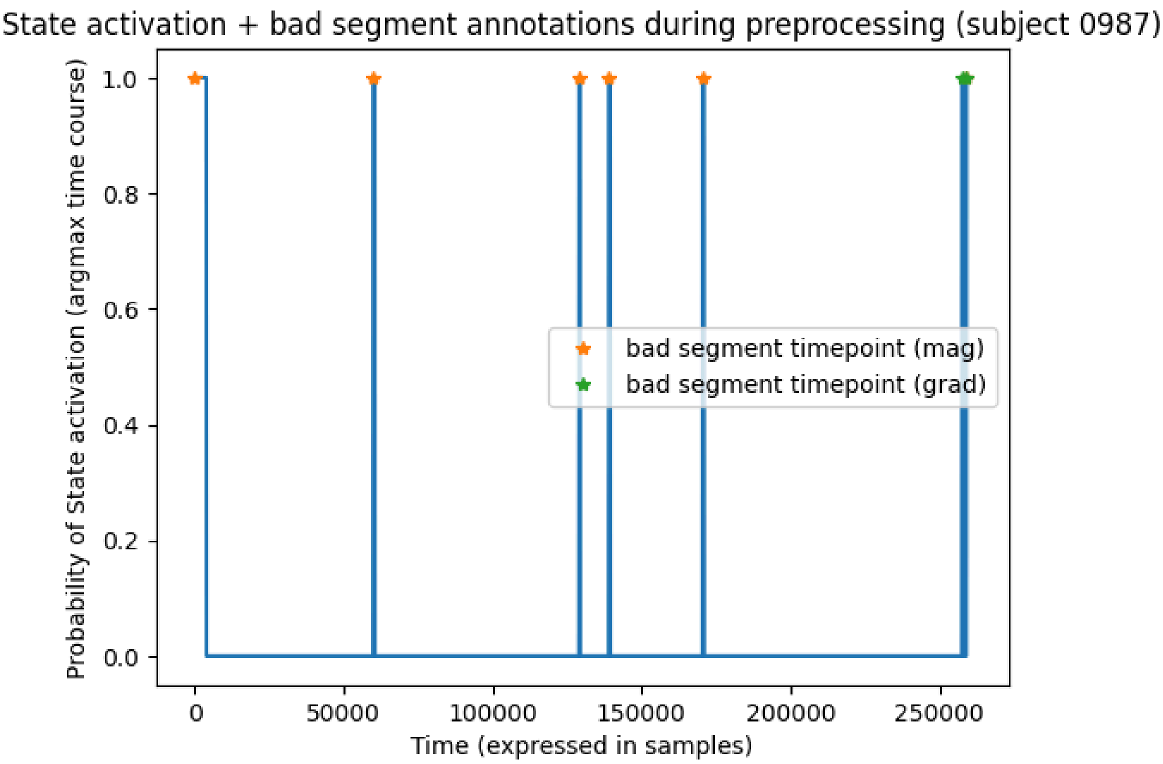
In [54]:
```
for subject in range(np.shape(alpha)[0]):

    stc_single = stc[subject][:,idx_state_flat]

    plt.figure()
    plt.plot(stc_single)

    loaded = mne.io.read_raw_fif(input_data_HMM[subject], verbose=False)

    # Get annotations
    annotations = loaded.annotations

    # Find timepoints with 'bad_segment_mag' or 'bad_segment_grad' annotatic
    bad_segment_mag_idx = [i for i, description in enumerate(annotations.des
    bad_segment_grad_idx = [i for i, description in enumerate(annotations.de

    # Get timepoints corresponding to the indices
    bad_segment_mag_timepoints = annotations.onset[bad_segment_mag_idx]
    bad_segment_grad_timepoints = annotations.onset[bad_segment_grad_idx]

    bad_segment_mag_timepoints = [(timepoint - loaded.first_samp/250.0)*250.
    bad_segment_grad_timepoints = [(timepoint - loaded.first_samp/250.0)*250

    #print("Timepoints with 'bad_segment_mag' annotation:", bad_segment_mag_
    #print("Timepoints with 'bad_segment_grad' annotation:", bad_segment_gra

    #print(len(bad_segment_mag_timepoints))
    #print(len(bad_segment_grad_timepoints))

    plt.plot(bad_segment_mag_timepoints, np.ones_like(bad_segment_mag_timepc
    plt.plot(bad_segment_grad_timepoints, np.ones_like(bad_segment_grad_time
    plt.legend()
    plt.title(f'State activation + bad segment annotations during preprocess
    plt.xlabel('Time (expressed in samples)')
    plt.ylabel('Probability of State activation (argmax time course)')
    plt.show()
```

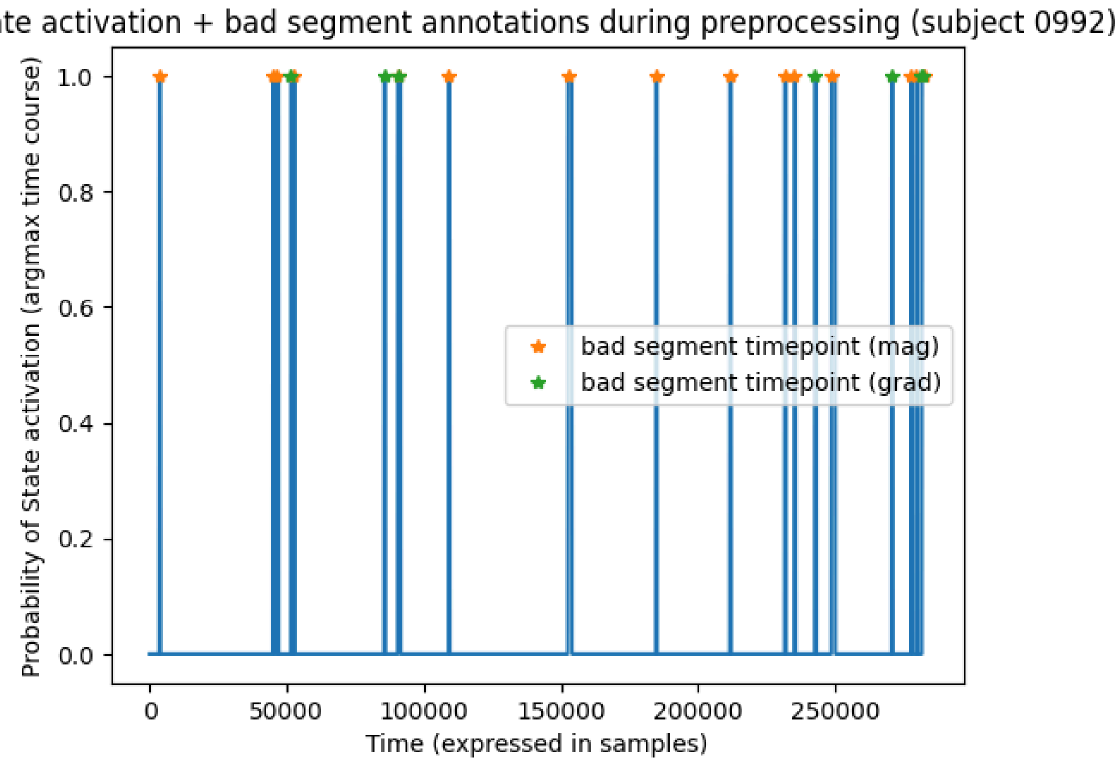


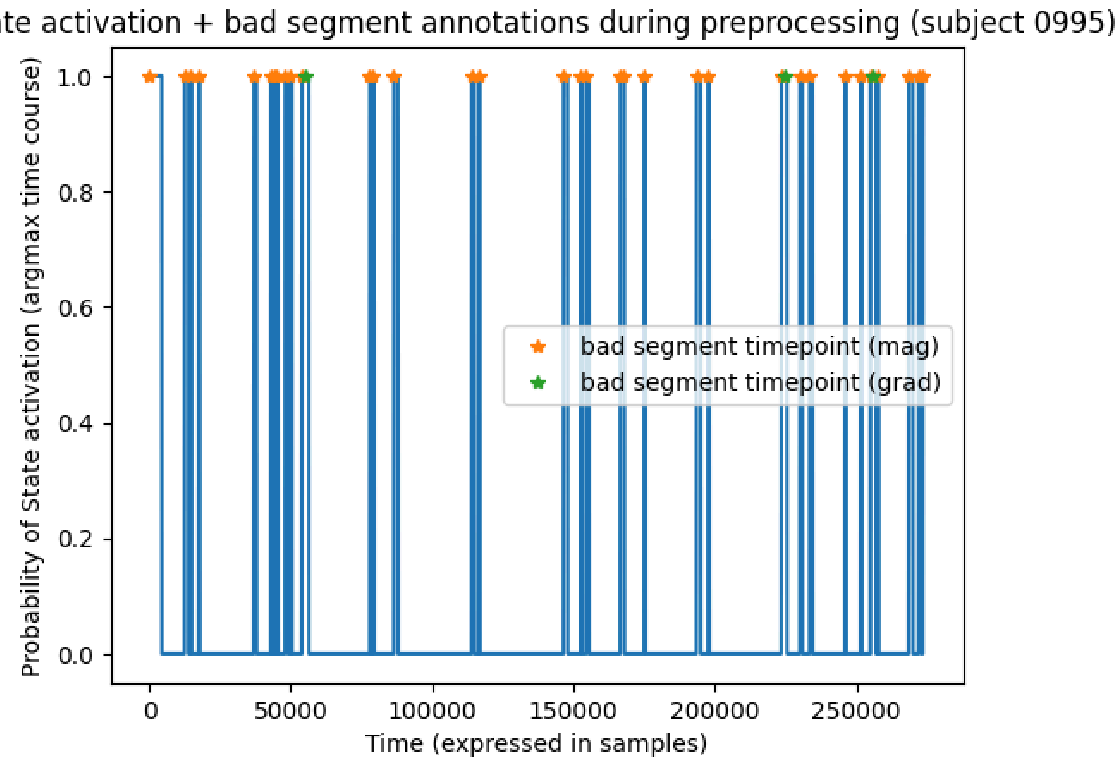

State activation + bad segment annotations during preprocessing (subject 0944)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
300000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)


State activation + bad segment annotations during preprocessing (subject 0945)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
300000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

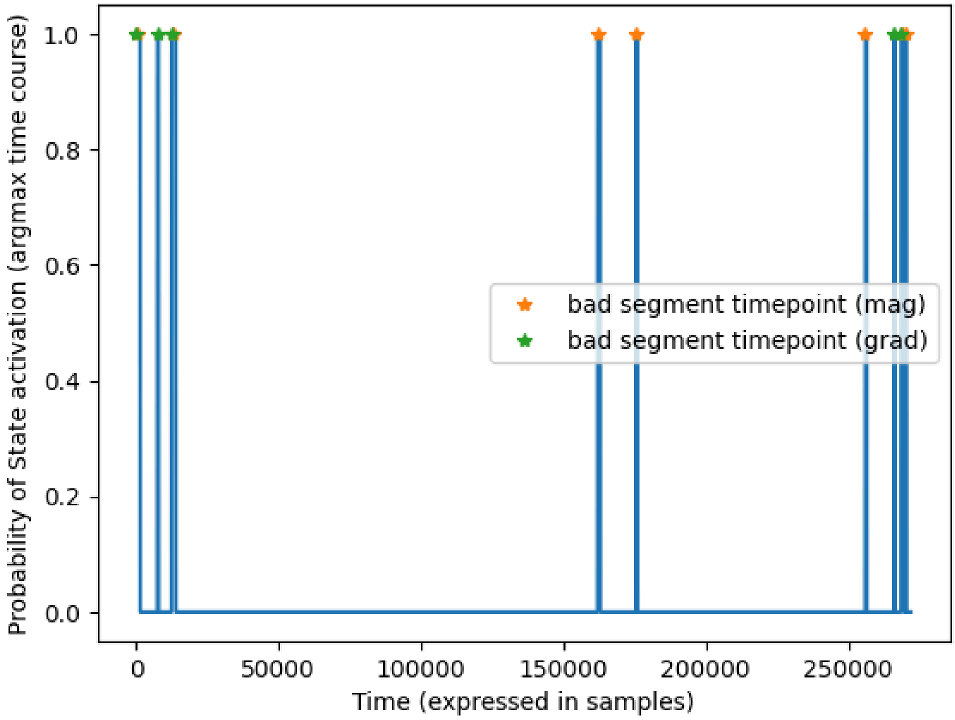

State activation + bad segment annotations during preprocessing (subject 0947)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
300000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)


State activation + bad segment annotations during preprocessing (subject 0987)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

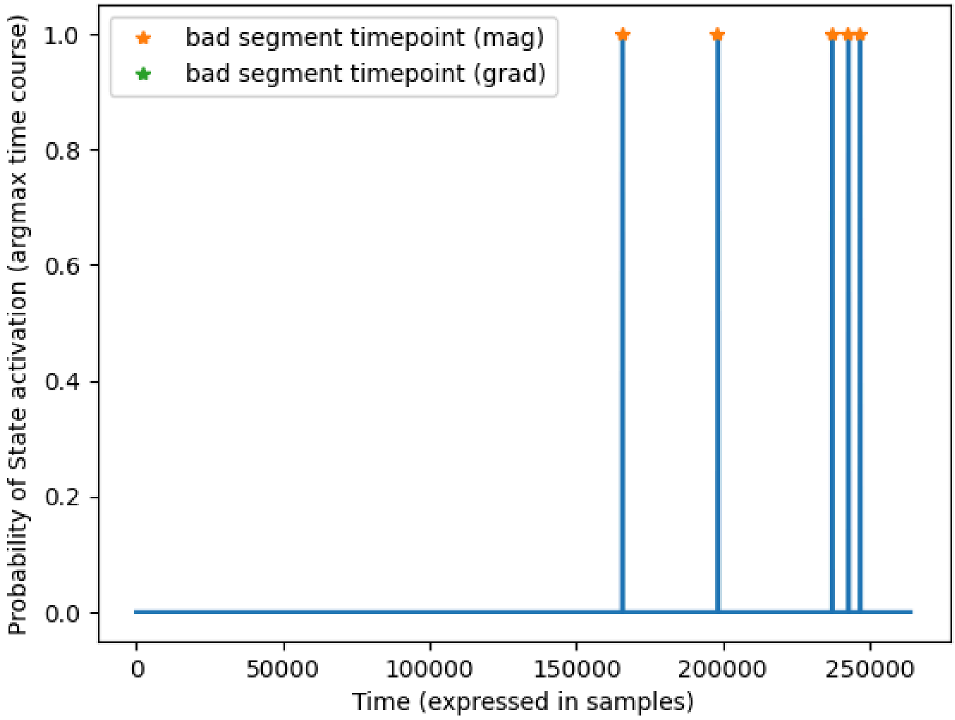

State activation + bad segment annotations during preprocessing (subject 0992)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

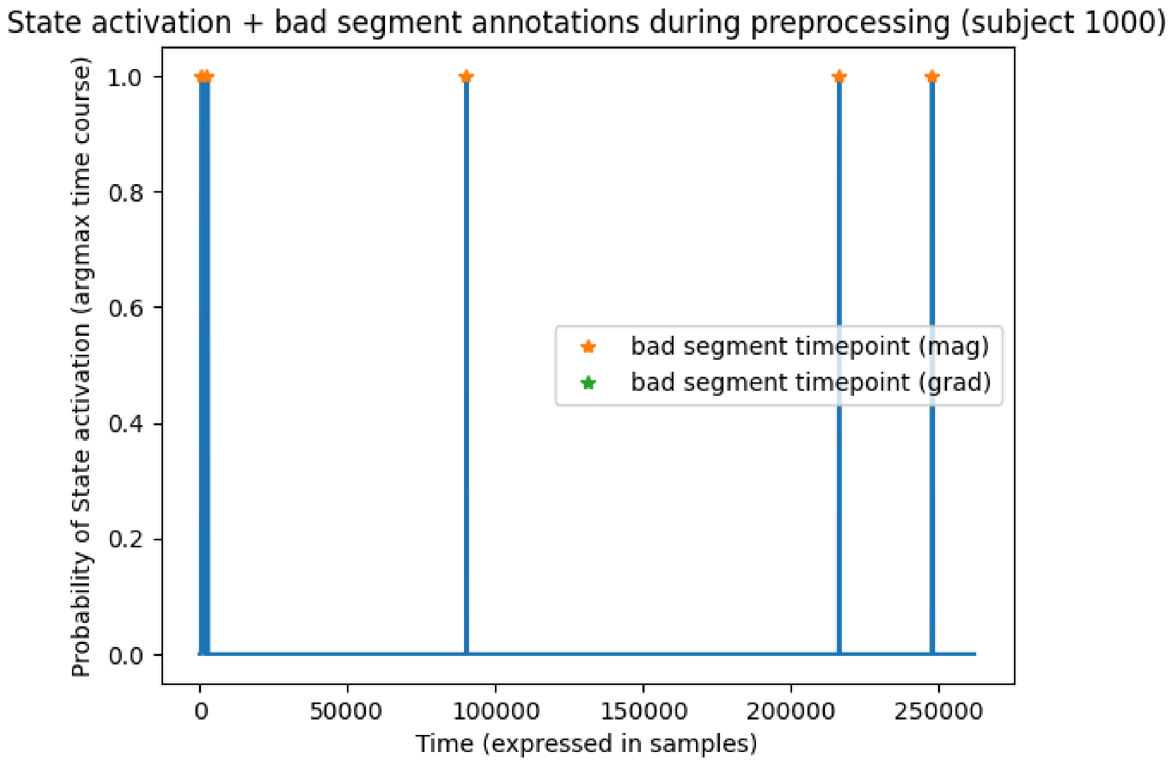

State activation + bad segment annotations during preprocessing (subject 0995)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

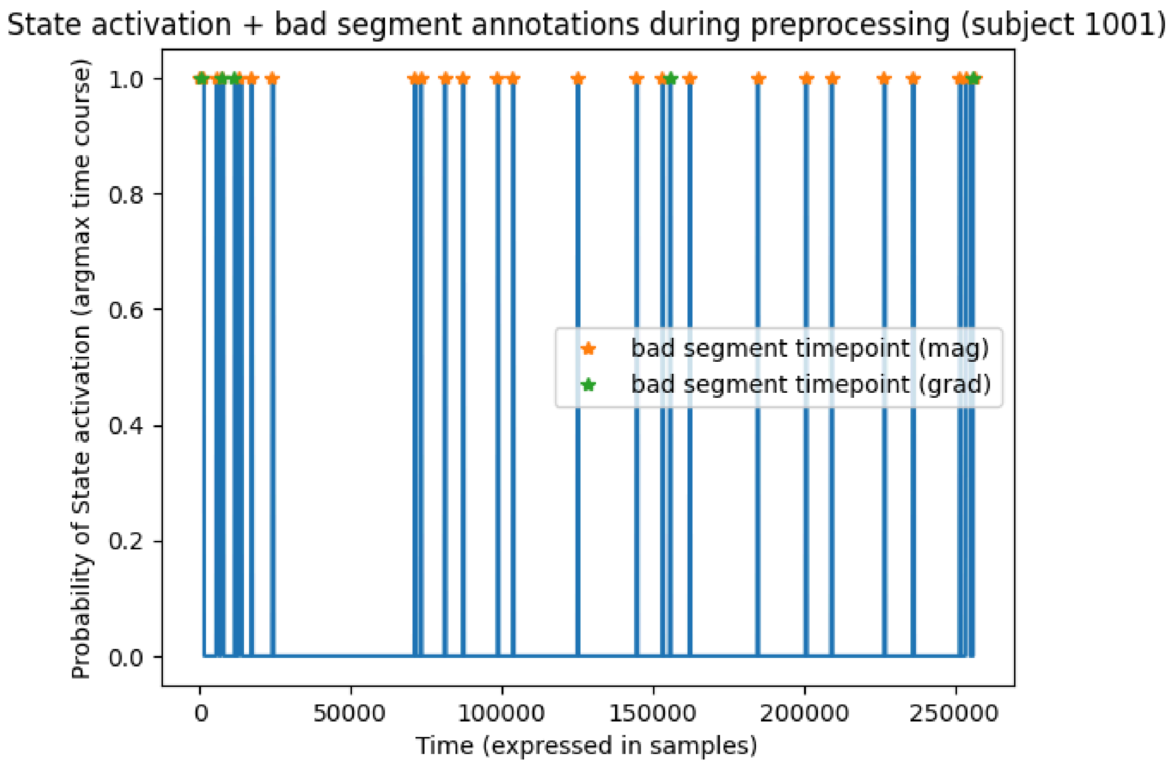
State activation + bad segment annotations during preprocessing (subject 0997)

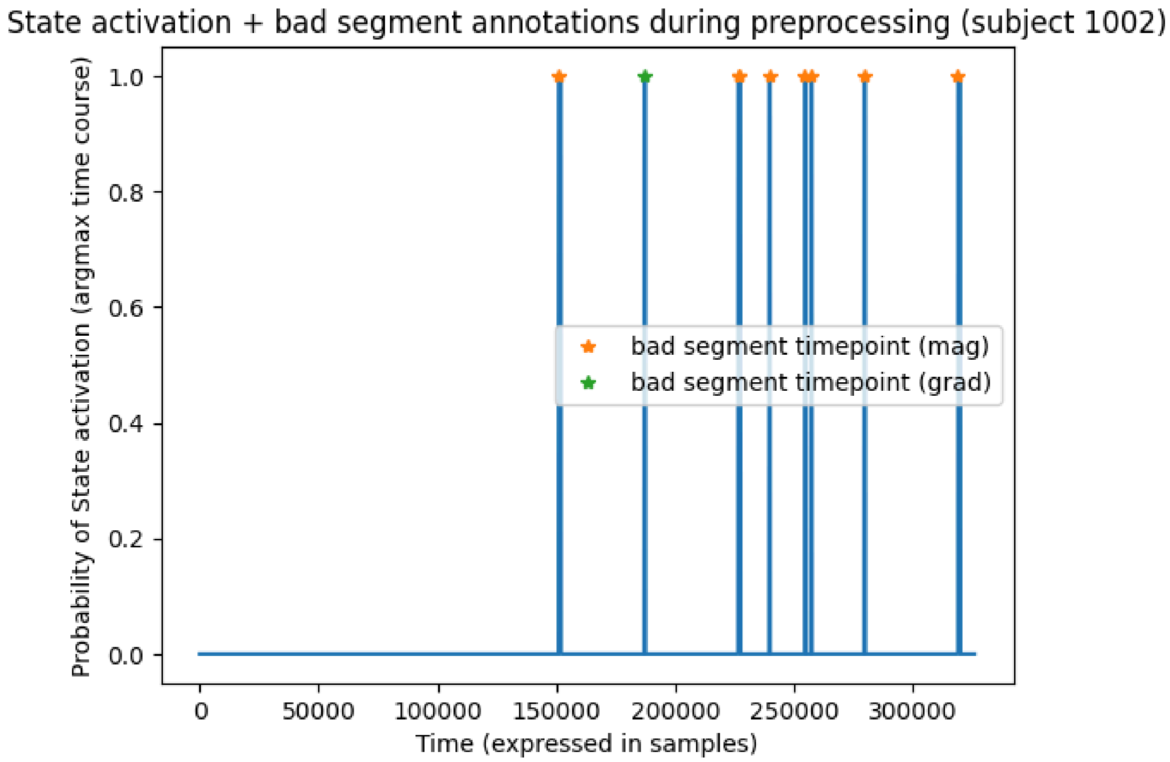


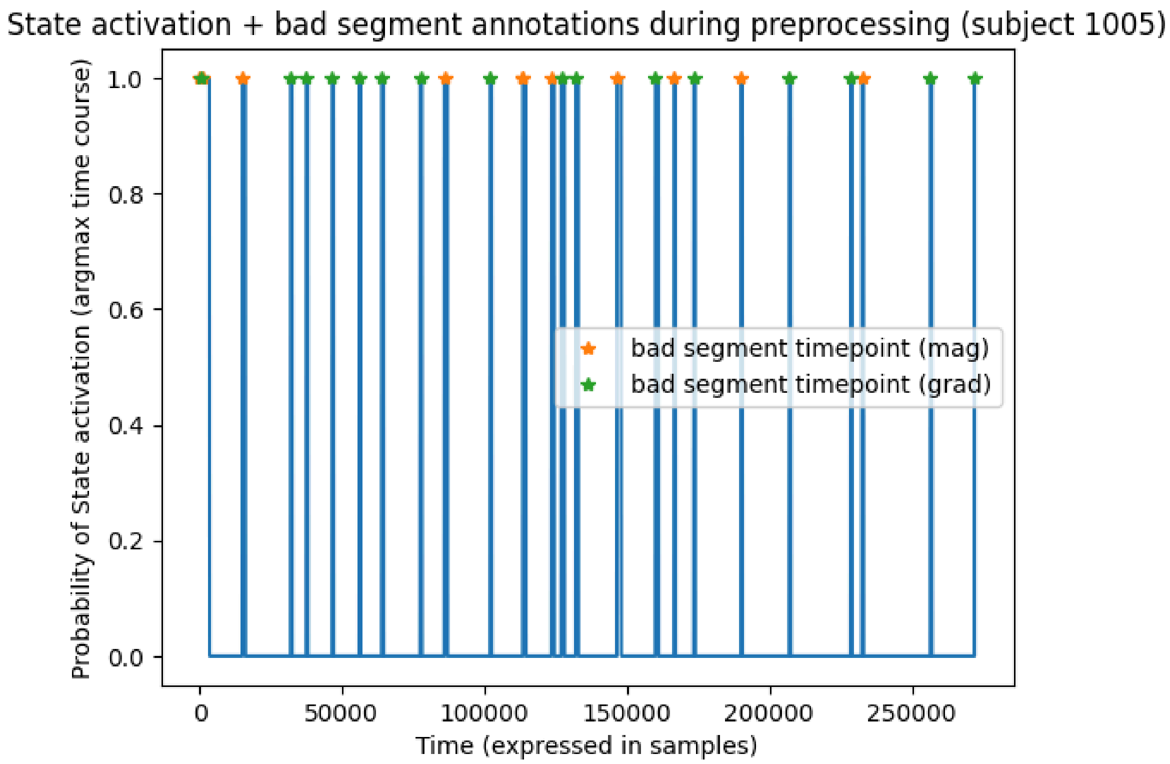
State activation + bad segment annotations during preprocessing (subject 0999)

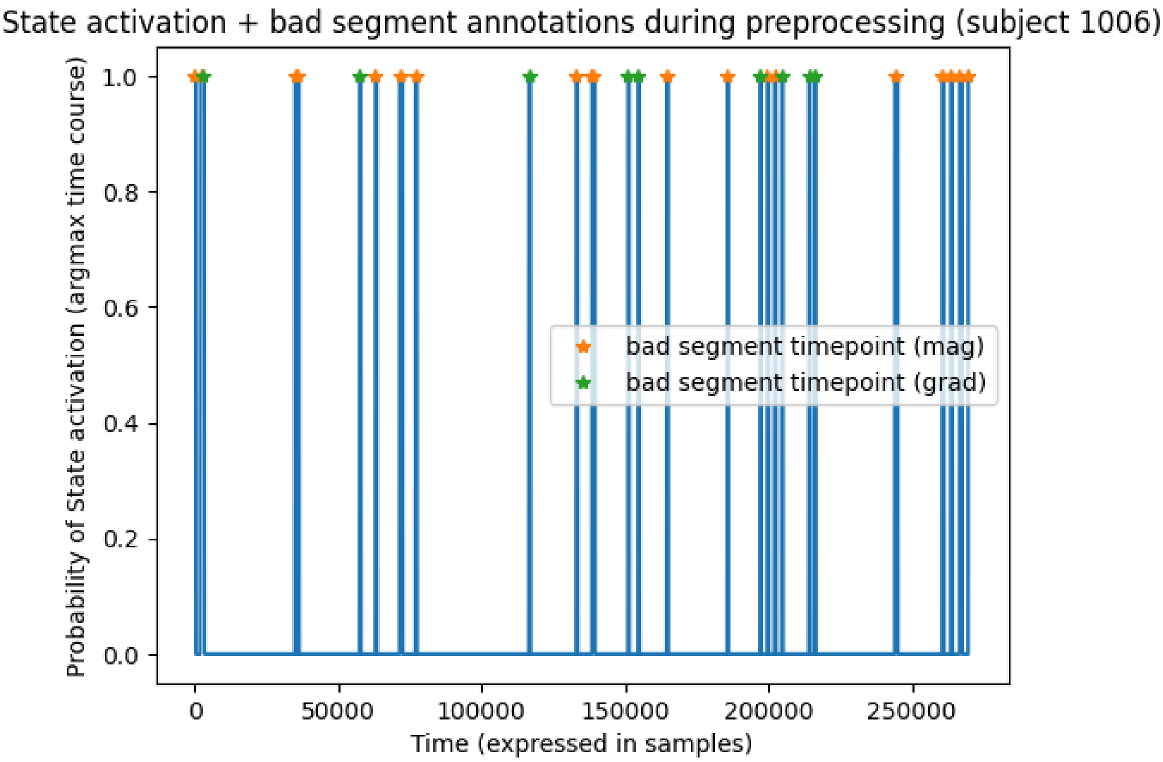


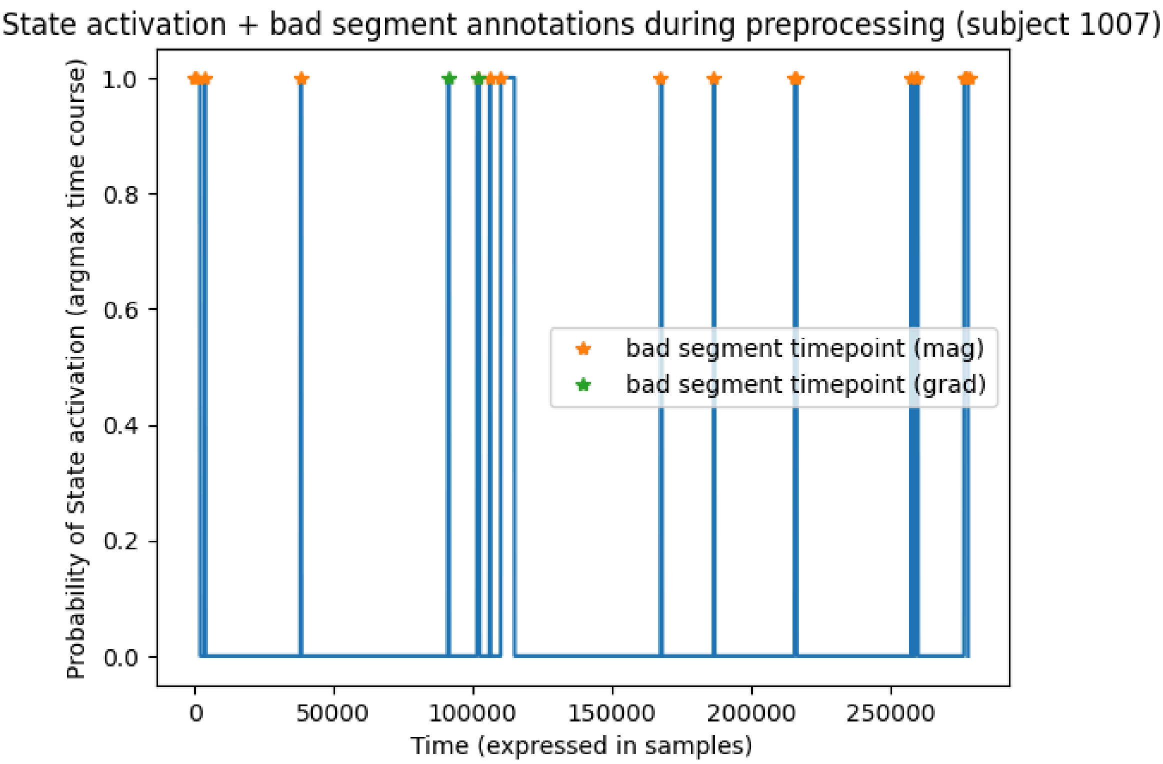

State activation + bad segment annotations during preprocessing (subject 1000)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
250000
Time (expressed in samples)

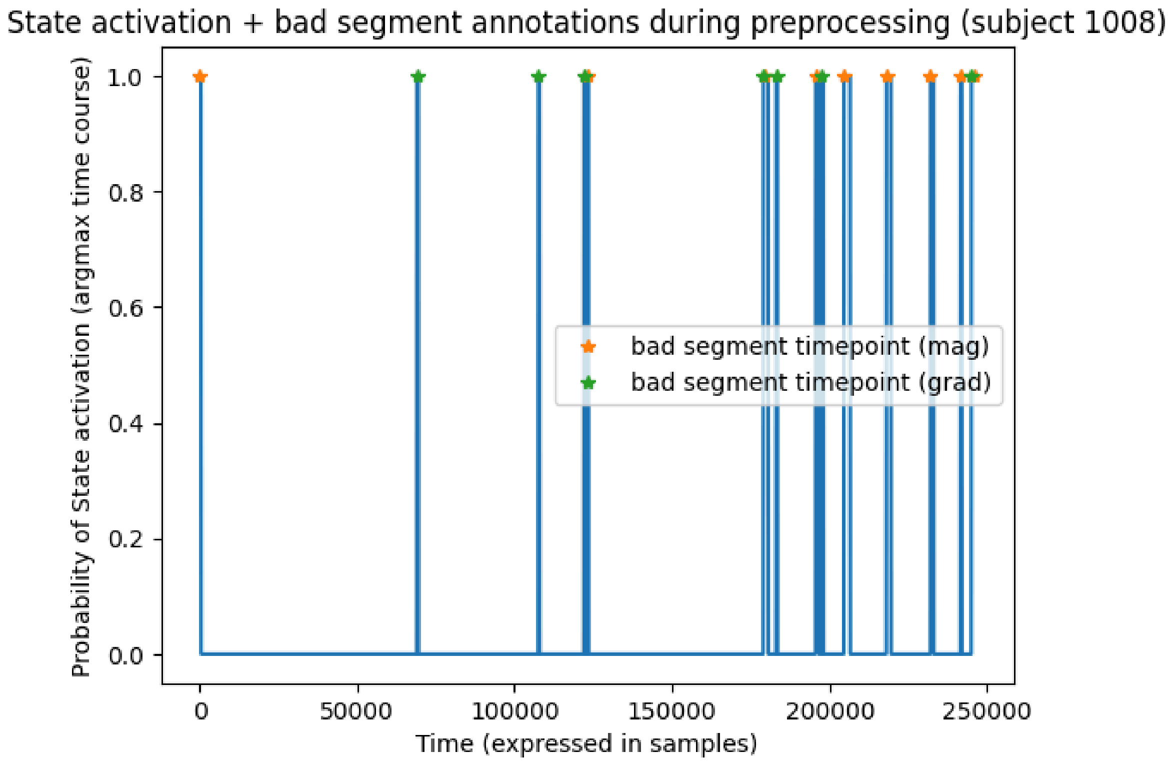

State activation + bad segment annotations during preprocessing (subject 1001)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
250000
Time (expressed in samples)

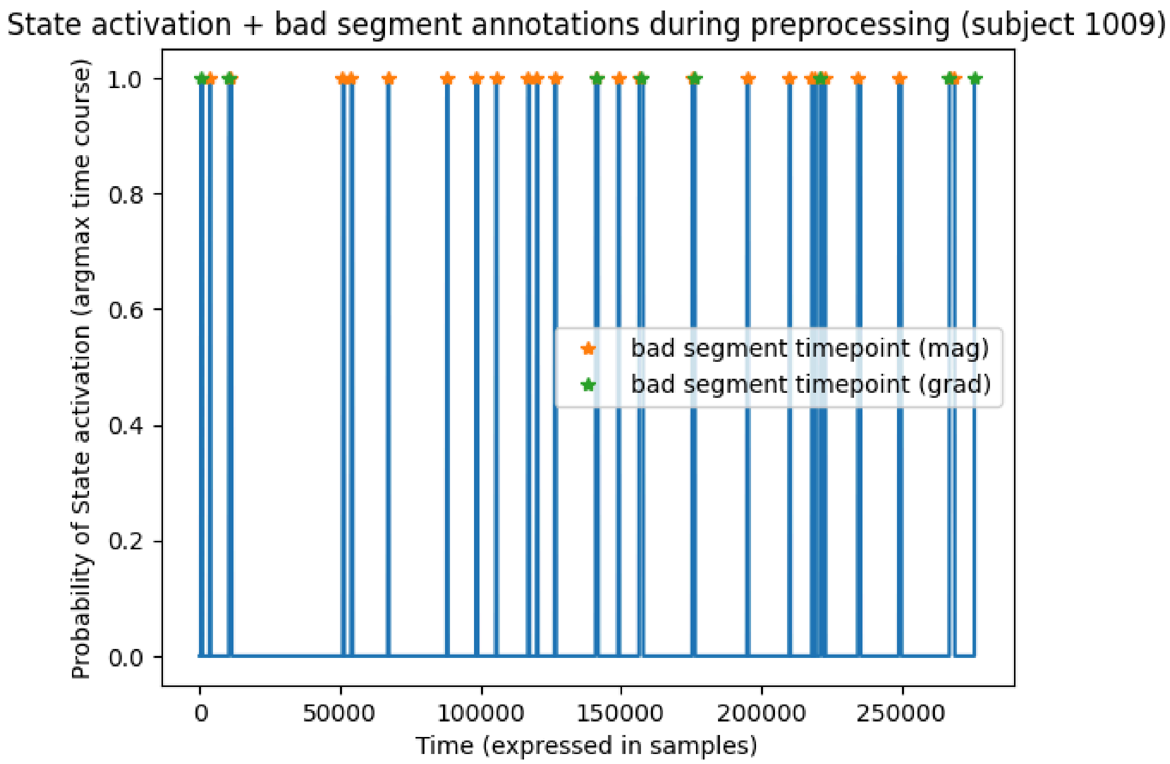

State activation + bad segment annotations during preprocessing (subject 1002)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
250000
300000
Time (expressed in samples)

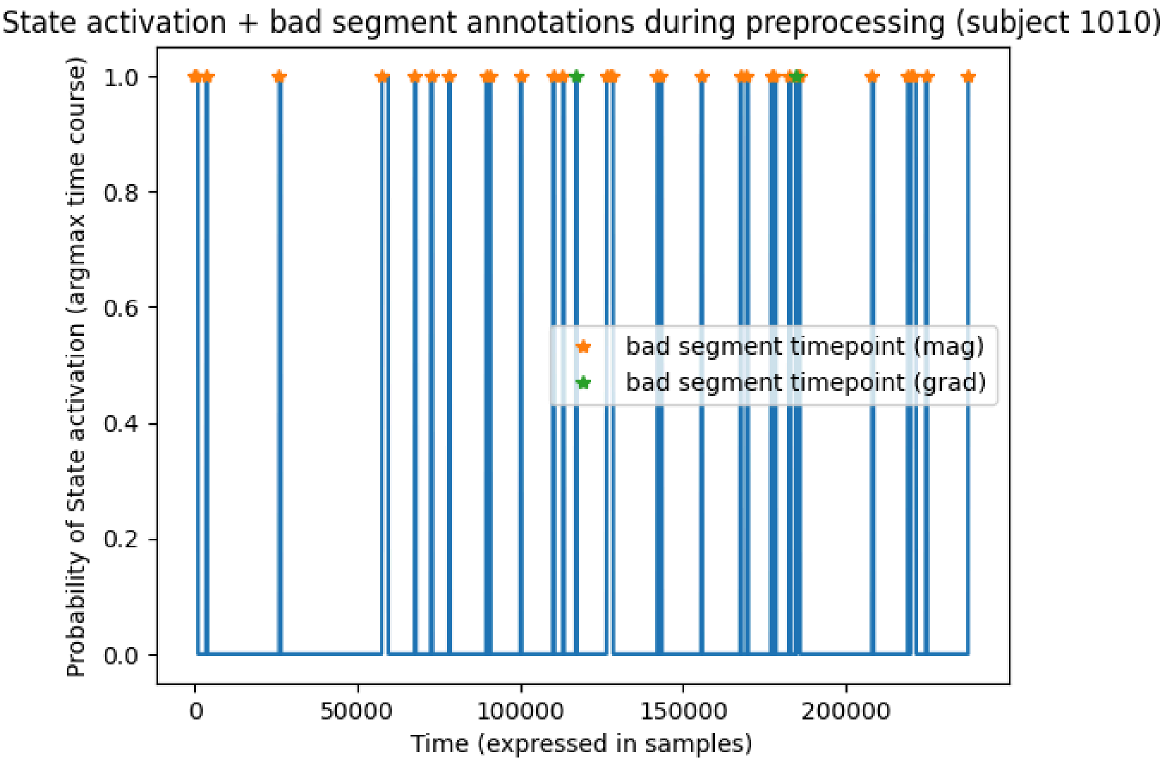

State activation + bad segment annotations during preprocessing (subject 1005)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
250000
Time (expressed in samples)

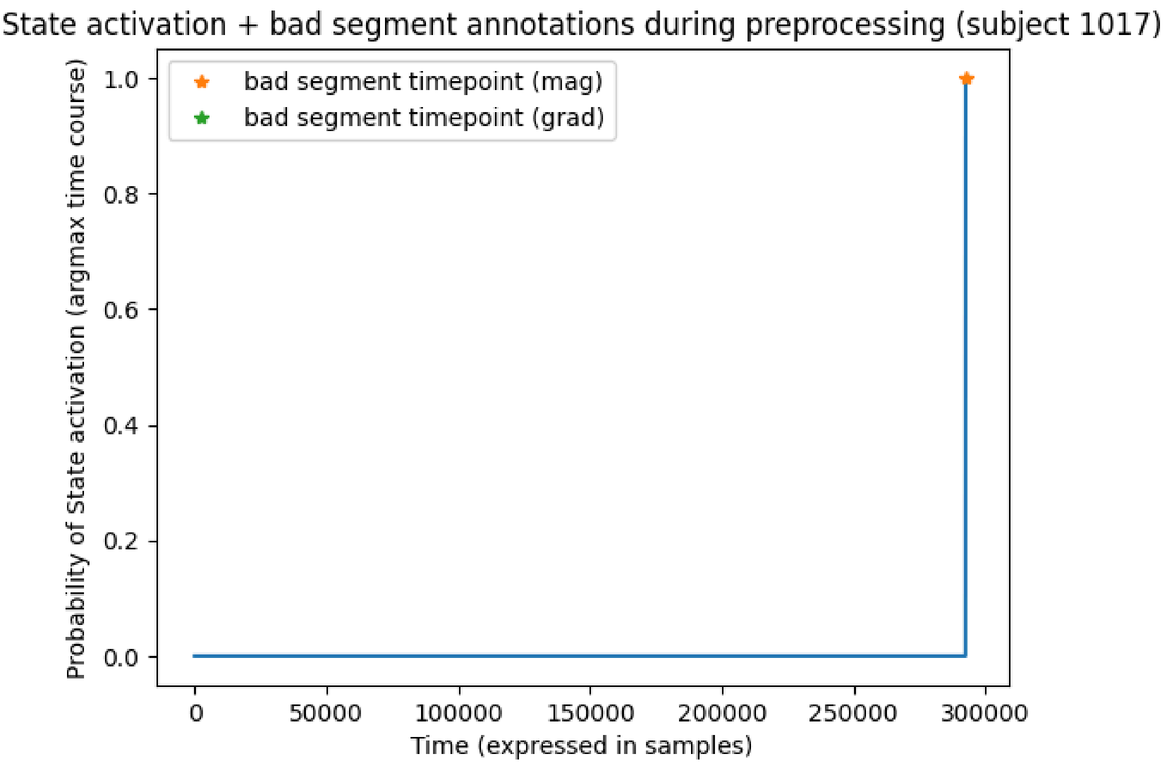

State activation + bad segment annotations during preprocessing (subject 1006)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
250000
Time (expressed in samples)

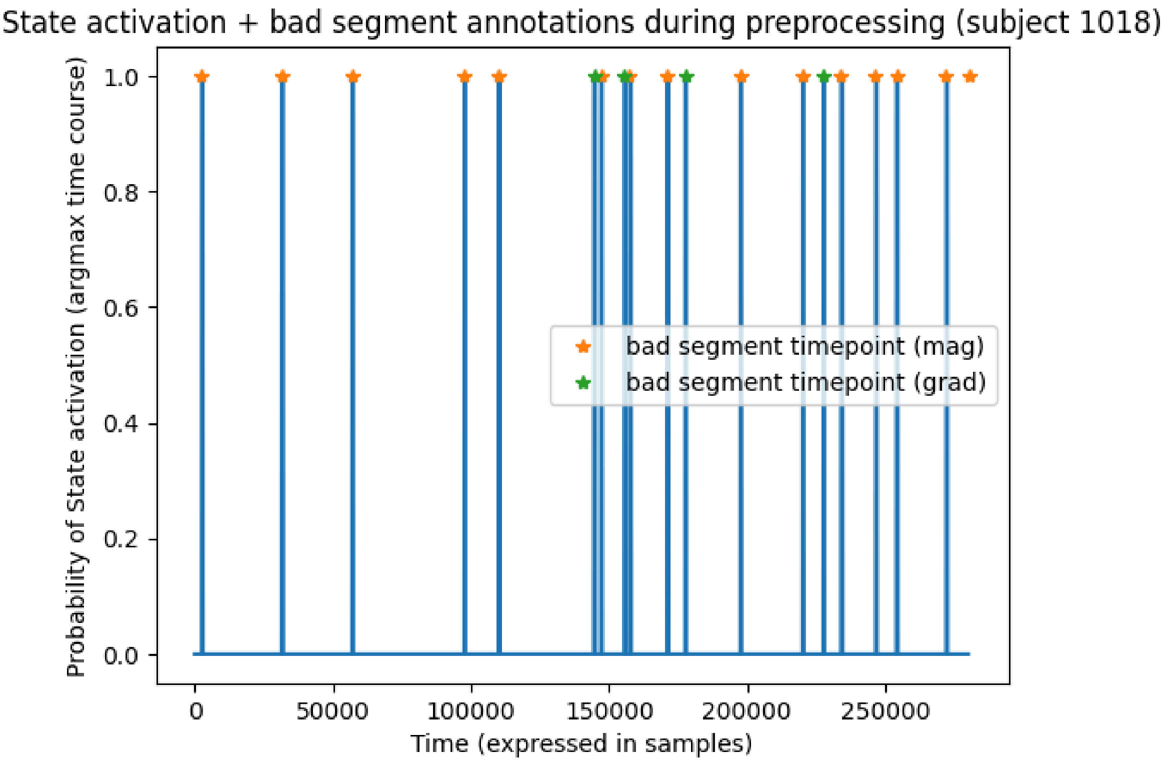

State activation + bad segment annotations during preprocessing (subject 1007)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
250000
Time (expressed in samples)

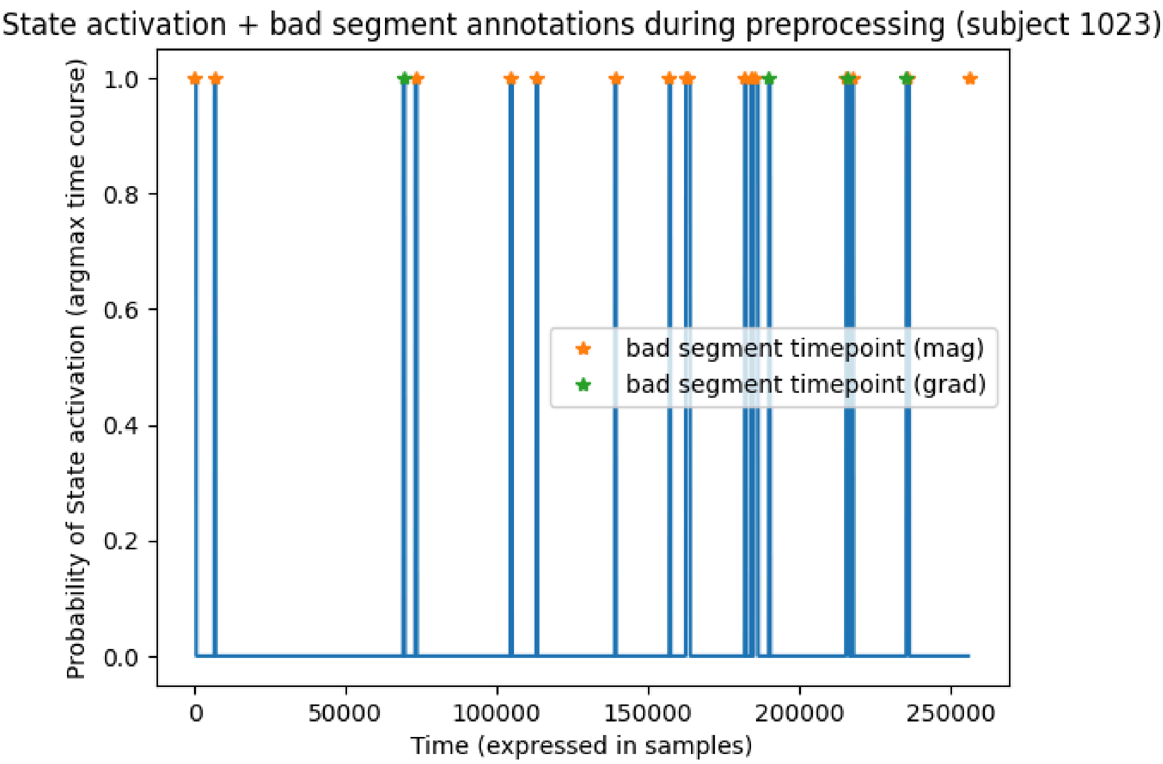

State activation + bad segment annotations during preprocessing (subject 1008)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

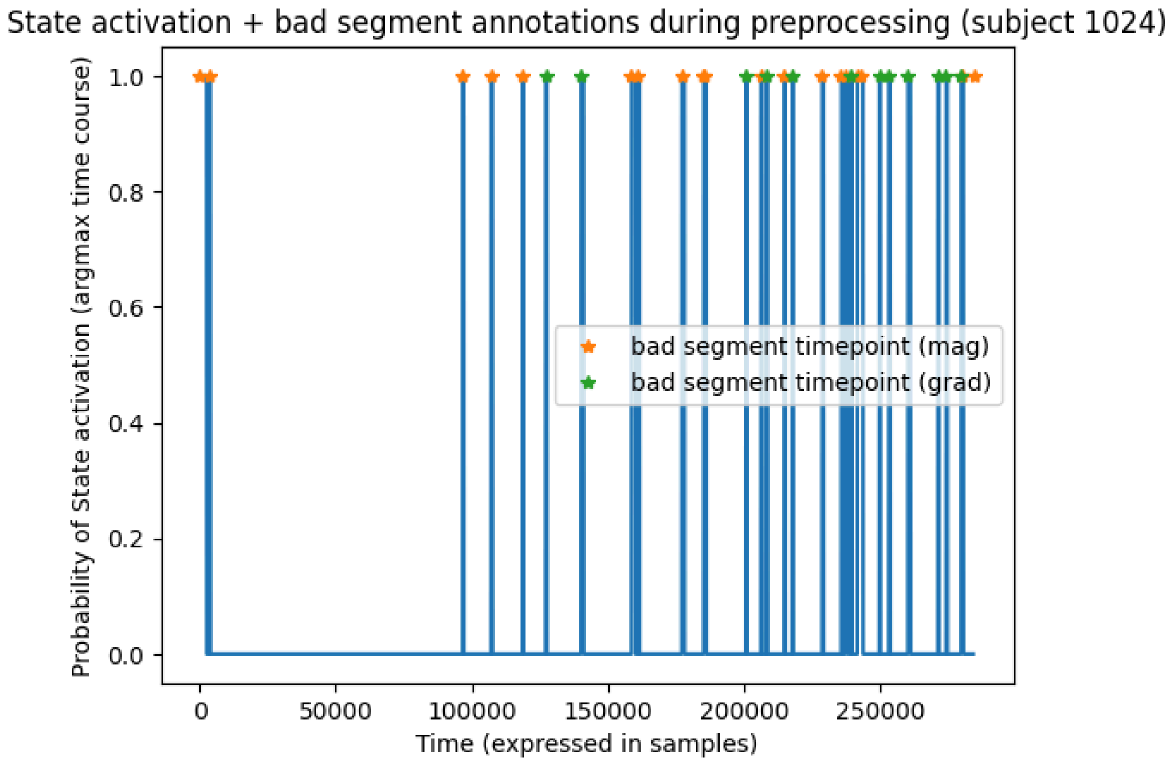

State activation + bad segment annotations during preprocessing (subject 1009)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

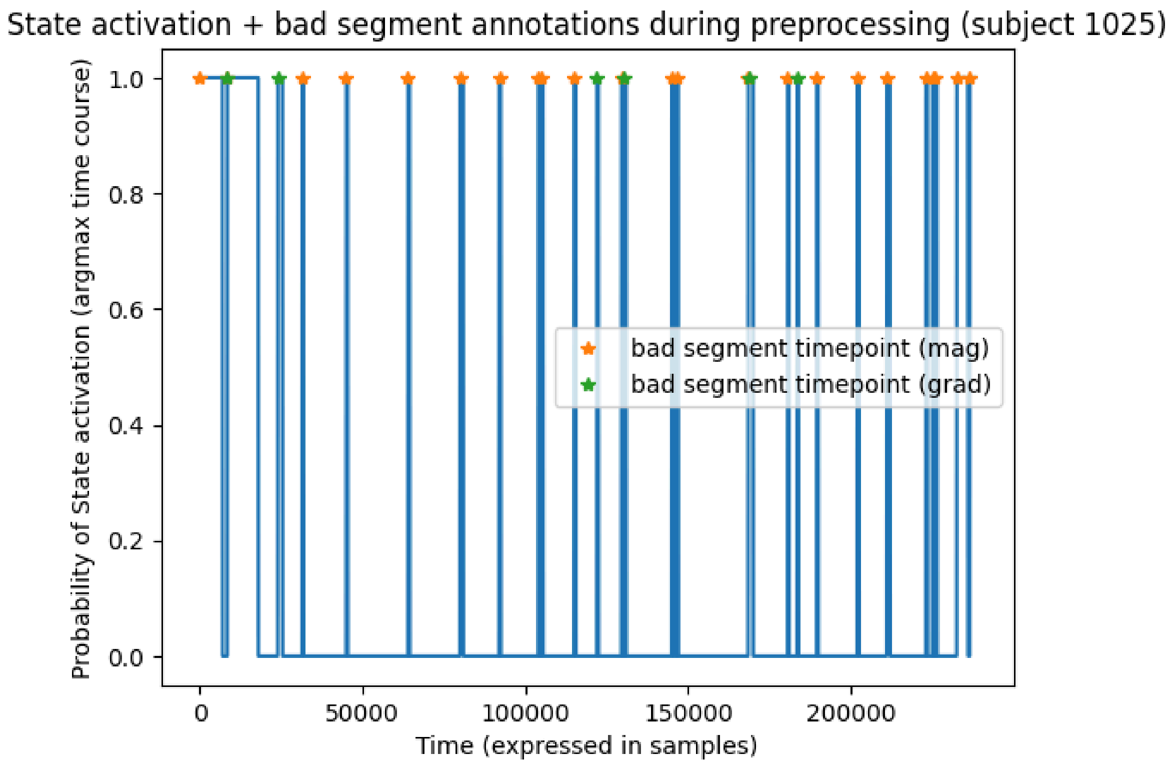

State activation + bad segment annotations during preprocessing (subject 1010)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
Time (expressed in samples)

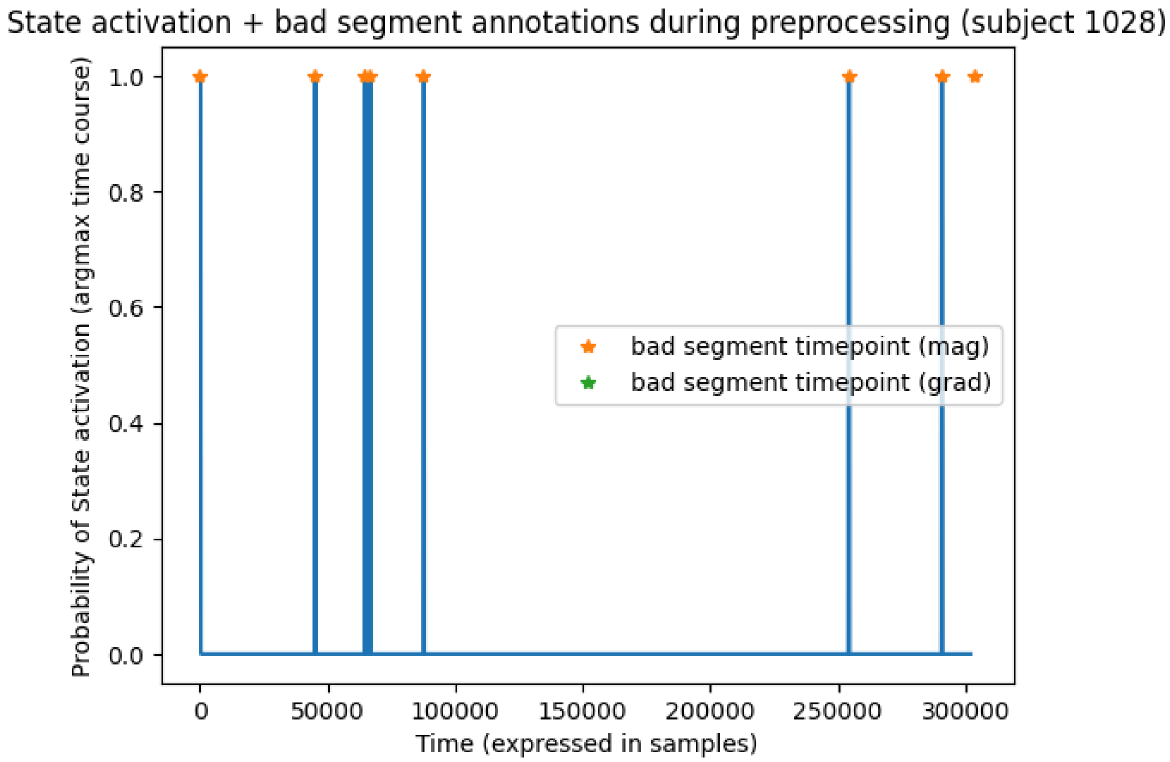

State activation + bad segment annotations during preprocessing (subject 1017)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
250000
300000
Time (expressed in samples)

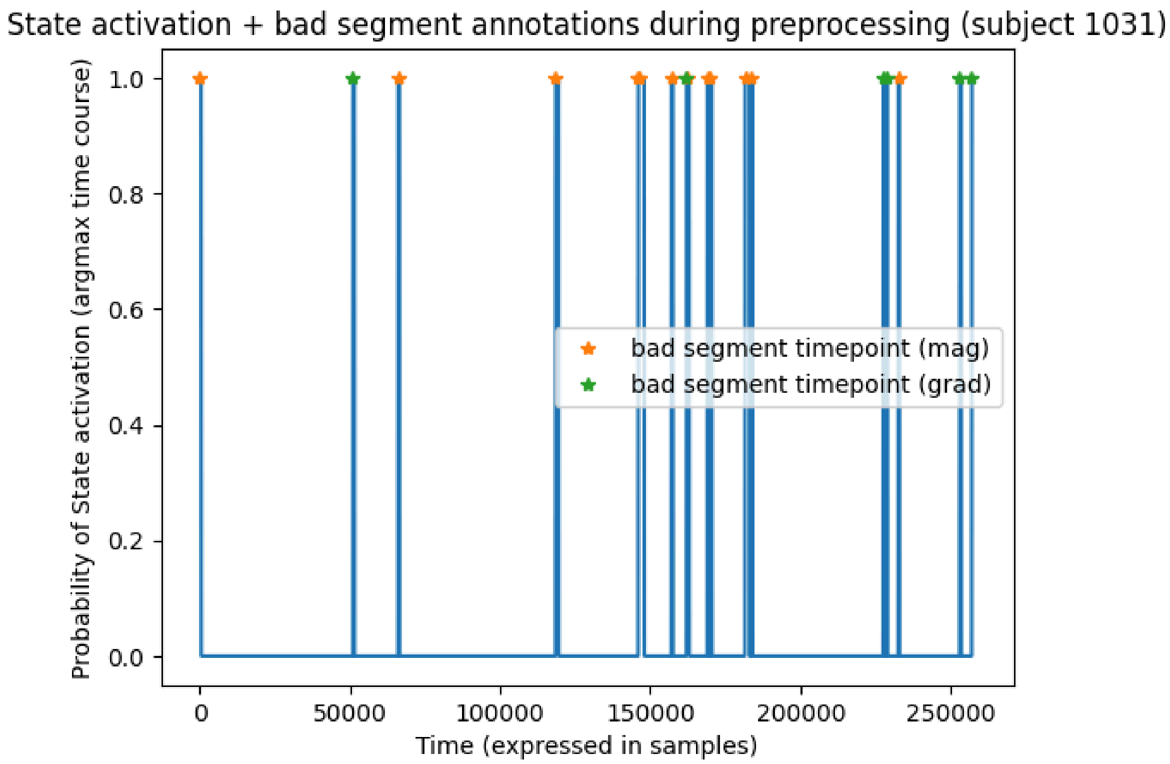

State activation + bad segment annotations during preprocessing (subject 1018)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
250000
Time (expressed in samples)

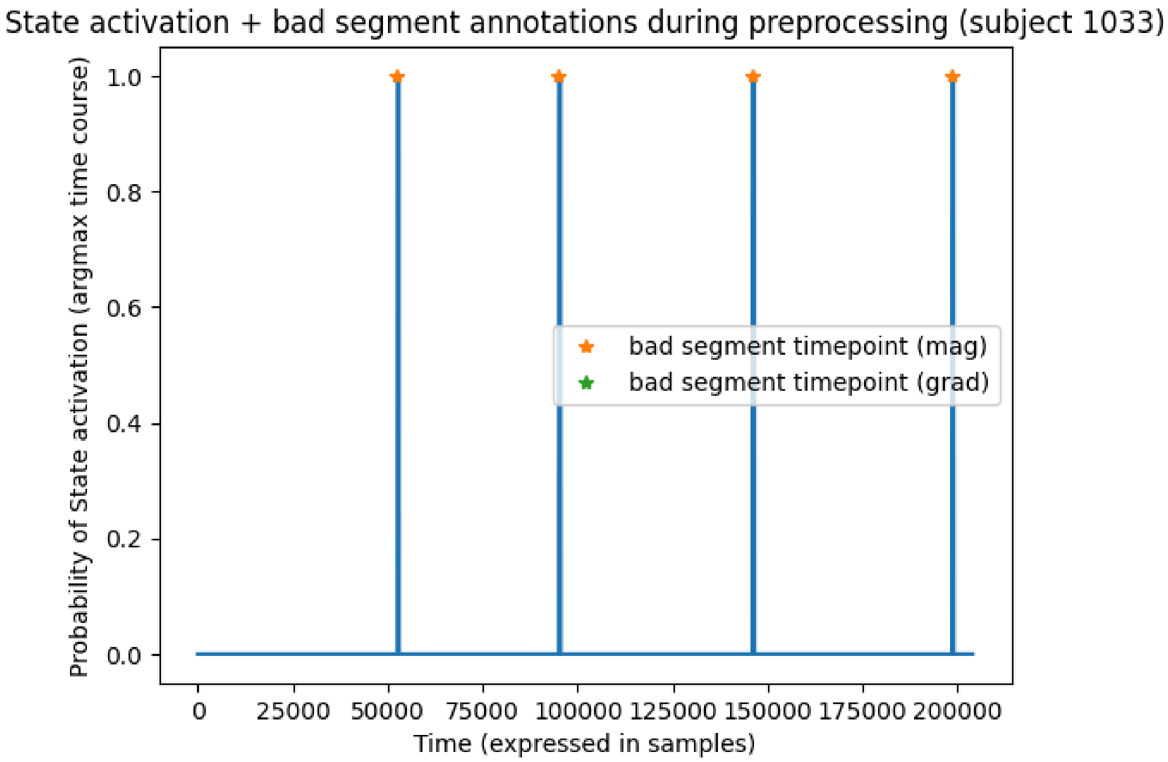

State activation + bad segment annotations during preprocessing (subject 1023)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
250000
Time (expressed in samples)

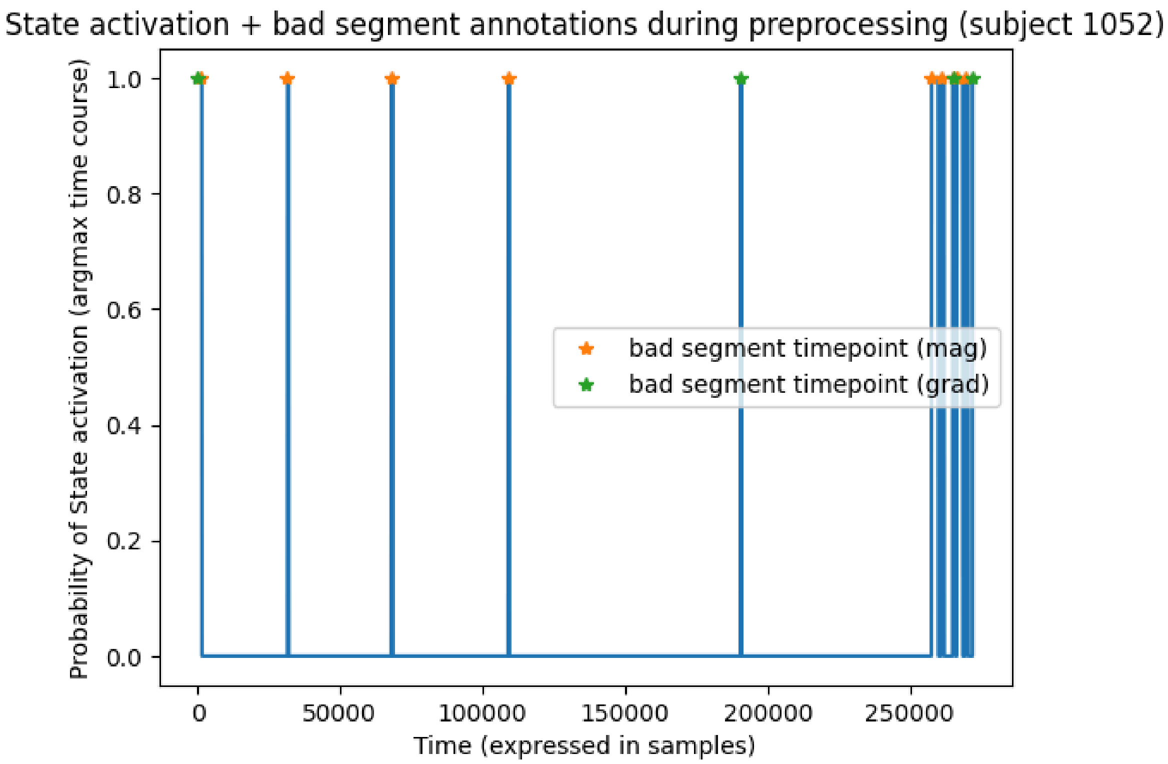

State activation + bad segment annotations during preprocessing (subject 1024)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

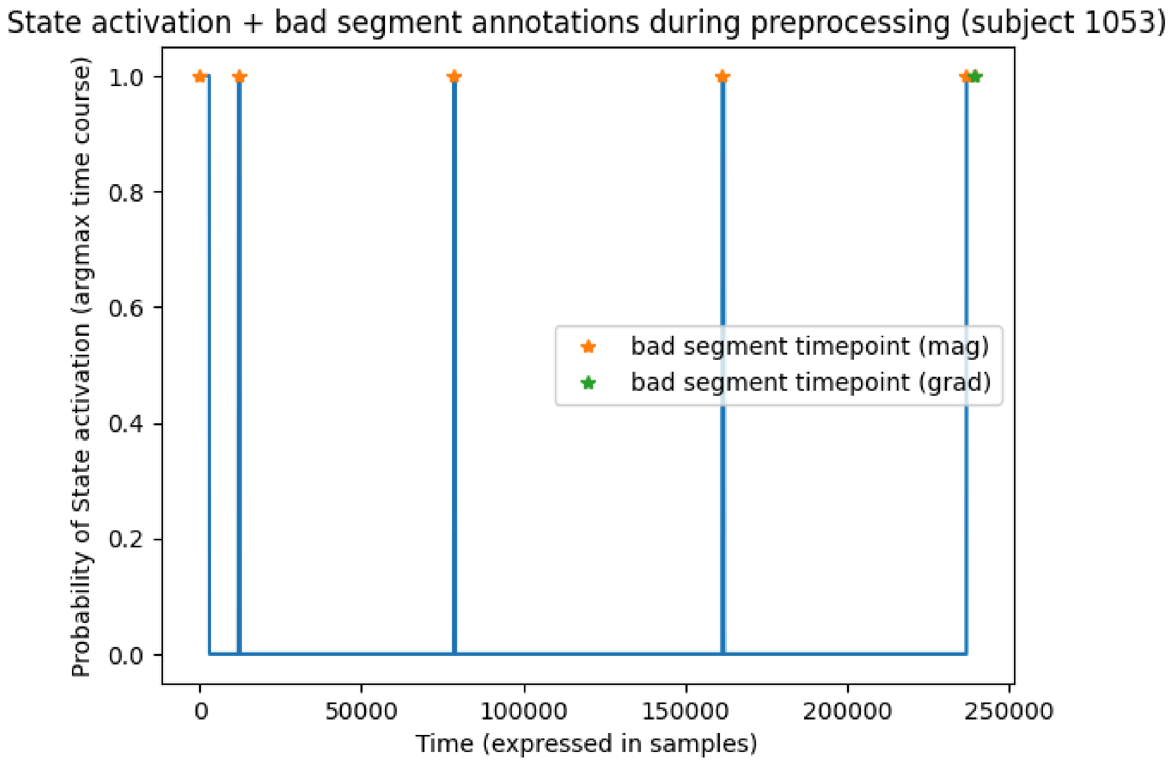

State activation + bad segment annotations during preprocessing (subject 1025)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

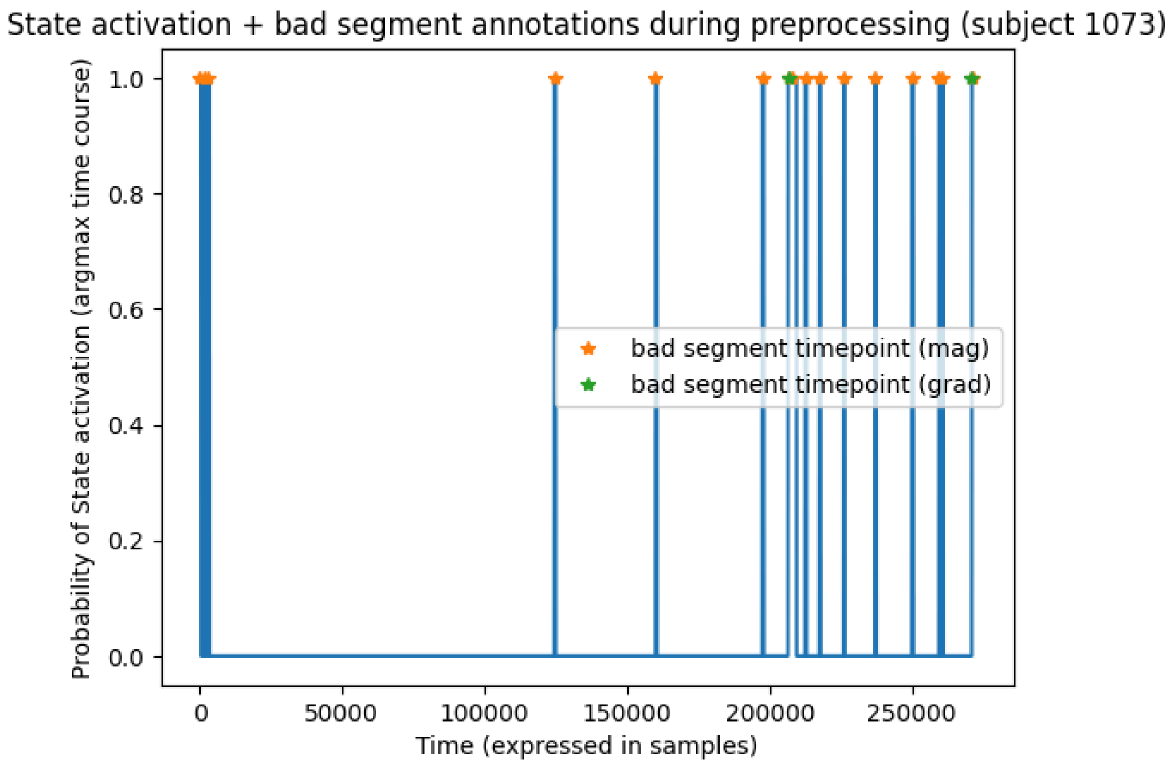

State activation + bad segment annotations during preprocessing (subject 1028)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
250000
300000
Time (expressed in samples)

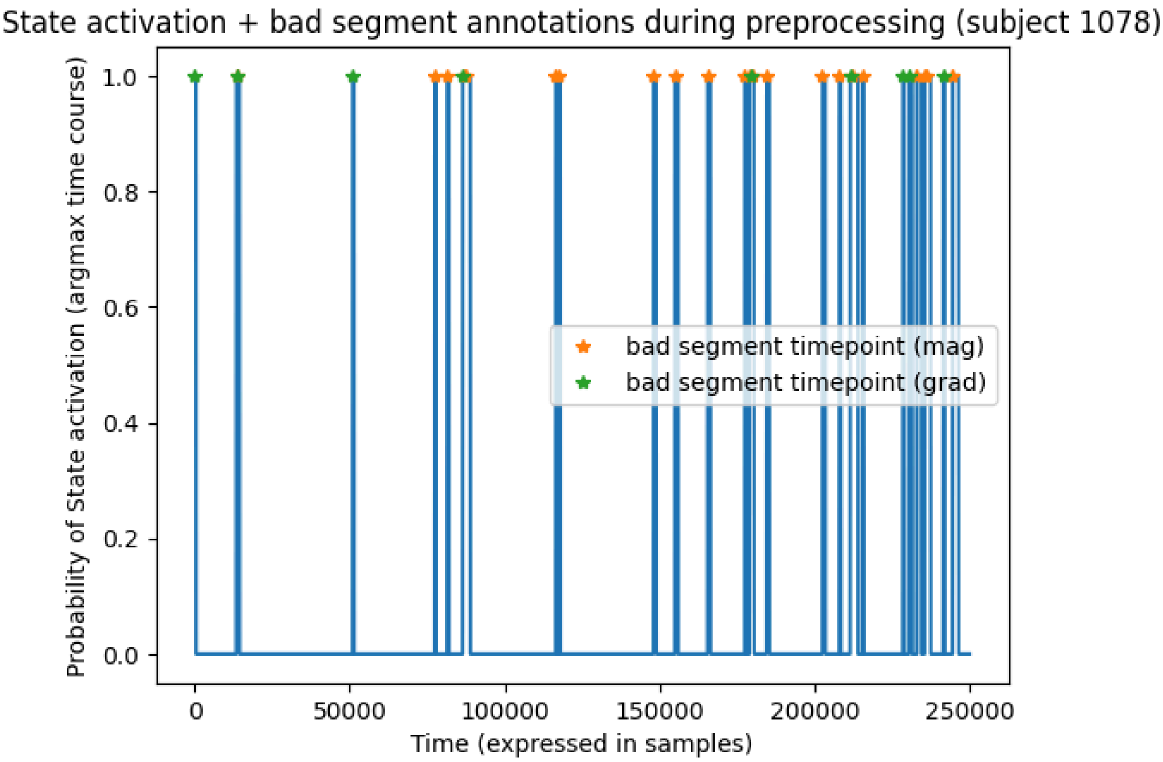

State activation + bad segment annotations during preprocessing (subject 1031)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
250000
Time (expressed in samples)

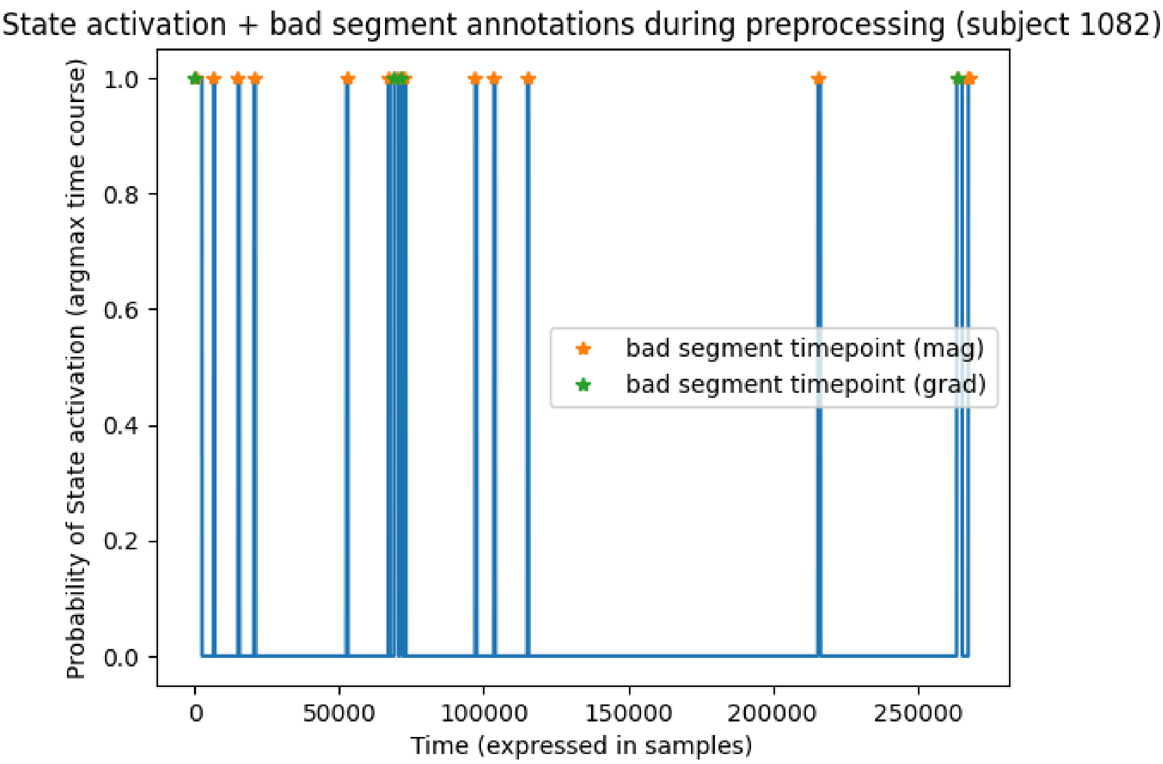

State activation + bad segment annotations during preprocessing (subject 1033)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
25000
50000
75000
100000
125000
150000
175000
200000
Time (expressed in samples)

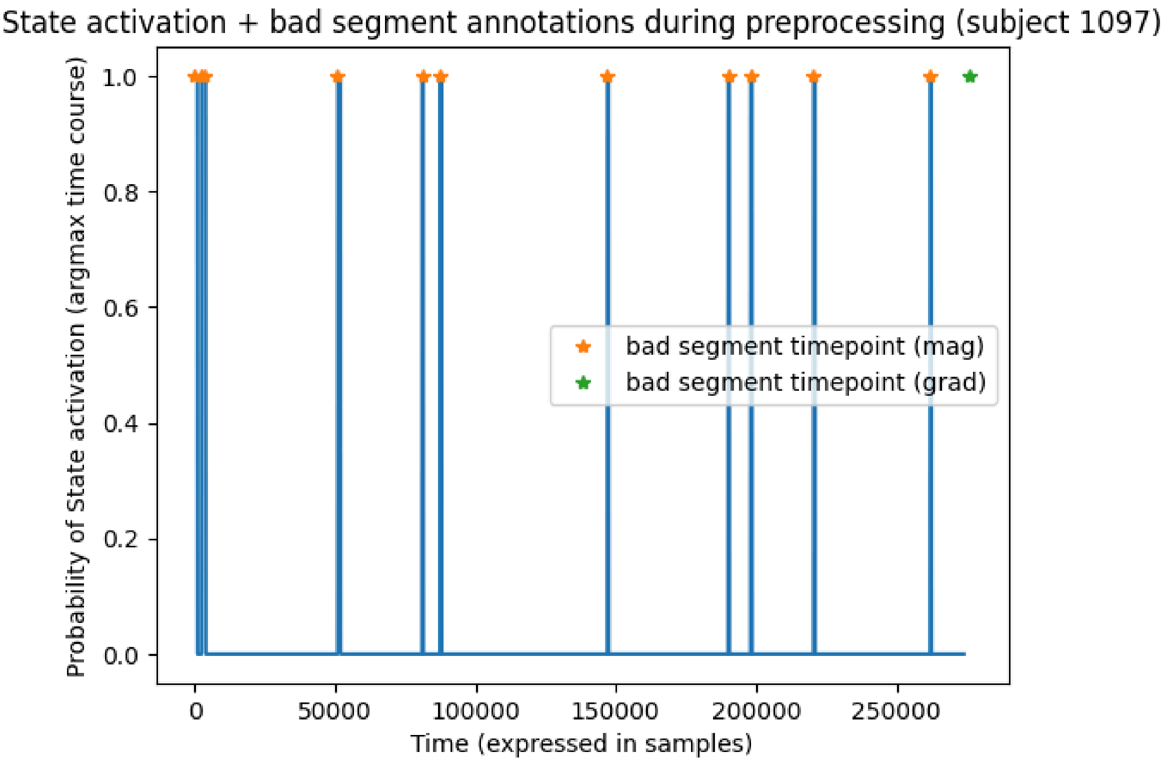

State activation + bad segment annotations during preprocessing (subject 1052)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
50000
100000
150000
200000
250000
Time (expressed in samples)

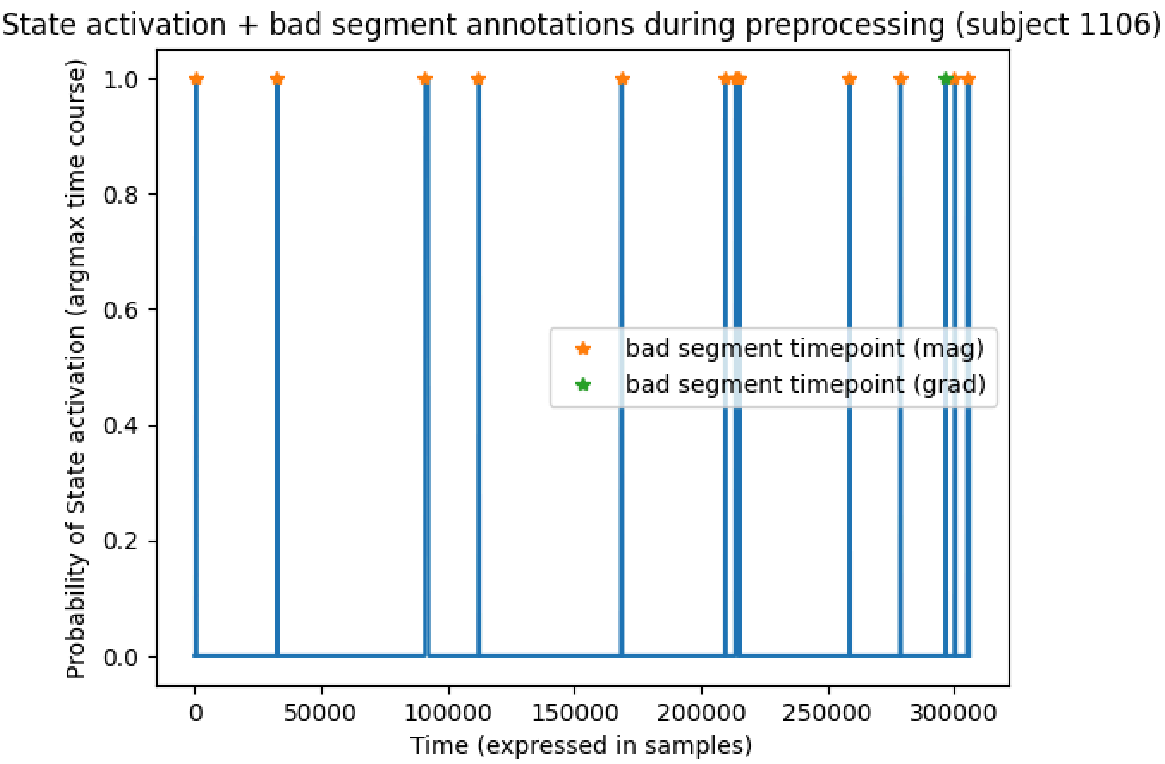

State activation + bad segment annotations during preprocessing (subject 1053)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

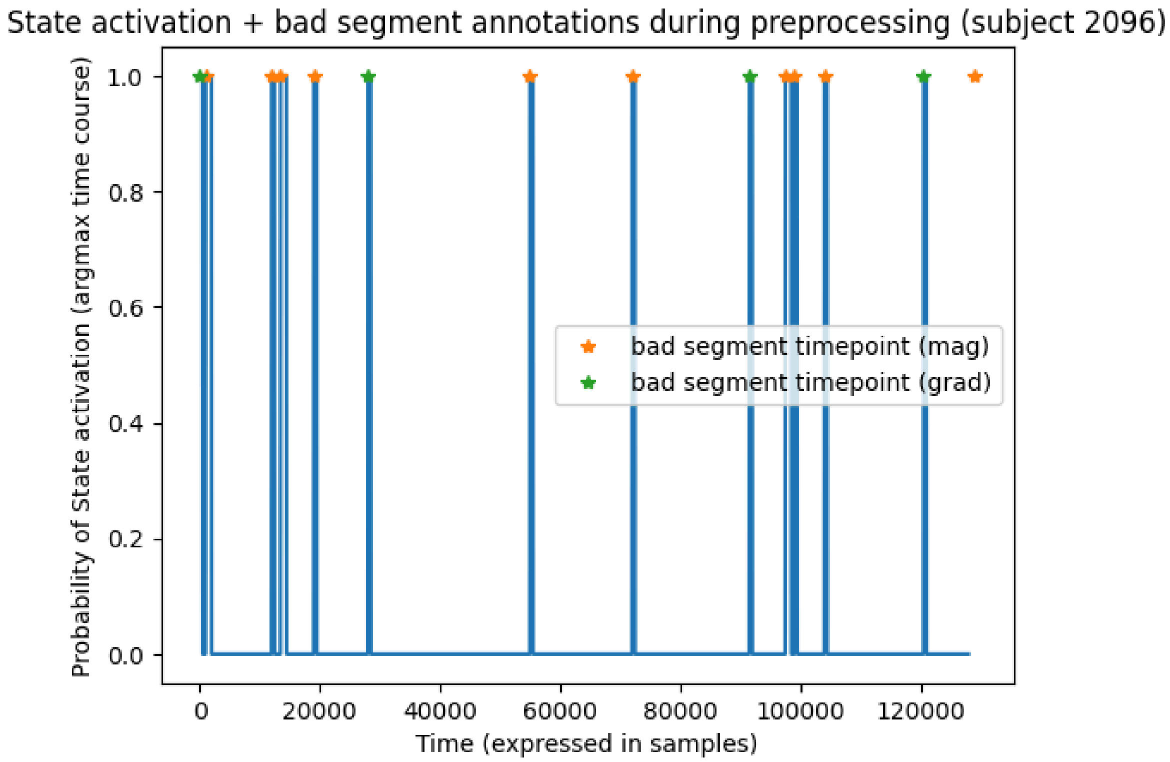

State activation + bad segment annotations during preprocessing (subject 1073)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

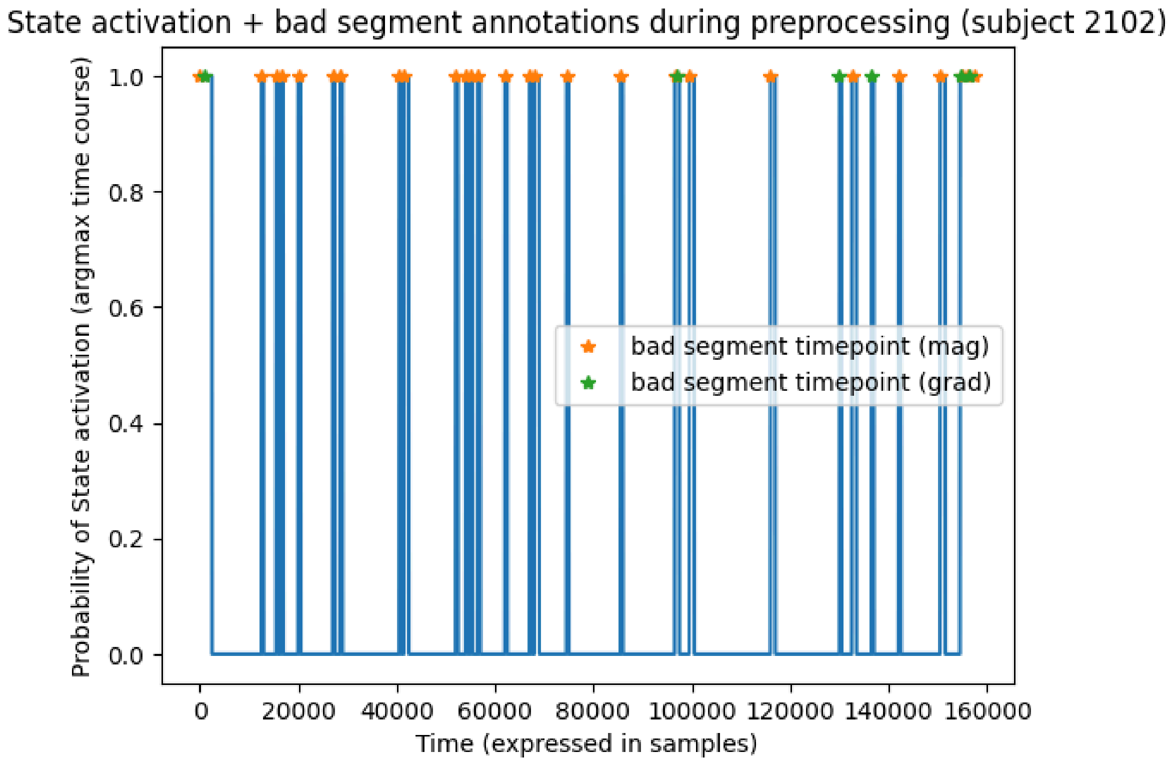

State activation + bad segment annotations during preprocessing (subject 1078)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

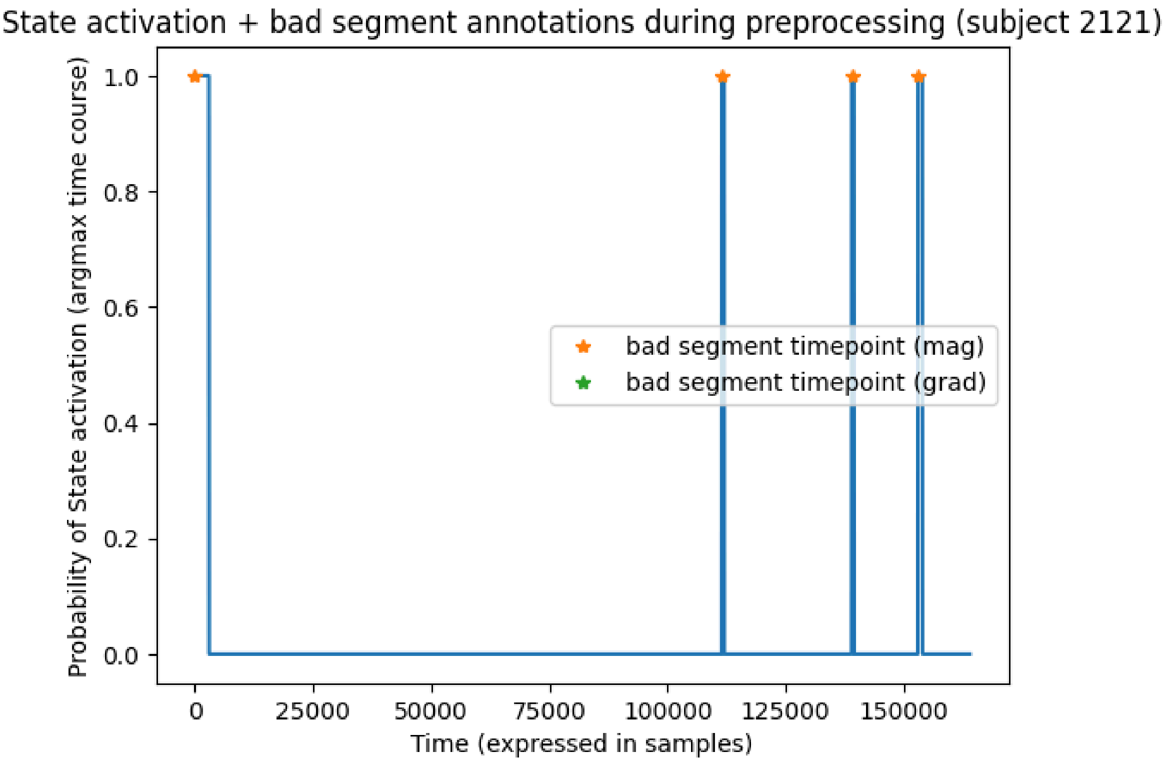

State activation + bad segment annotations during preprocessing (subject 1082)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

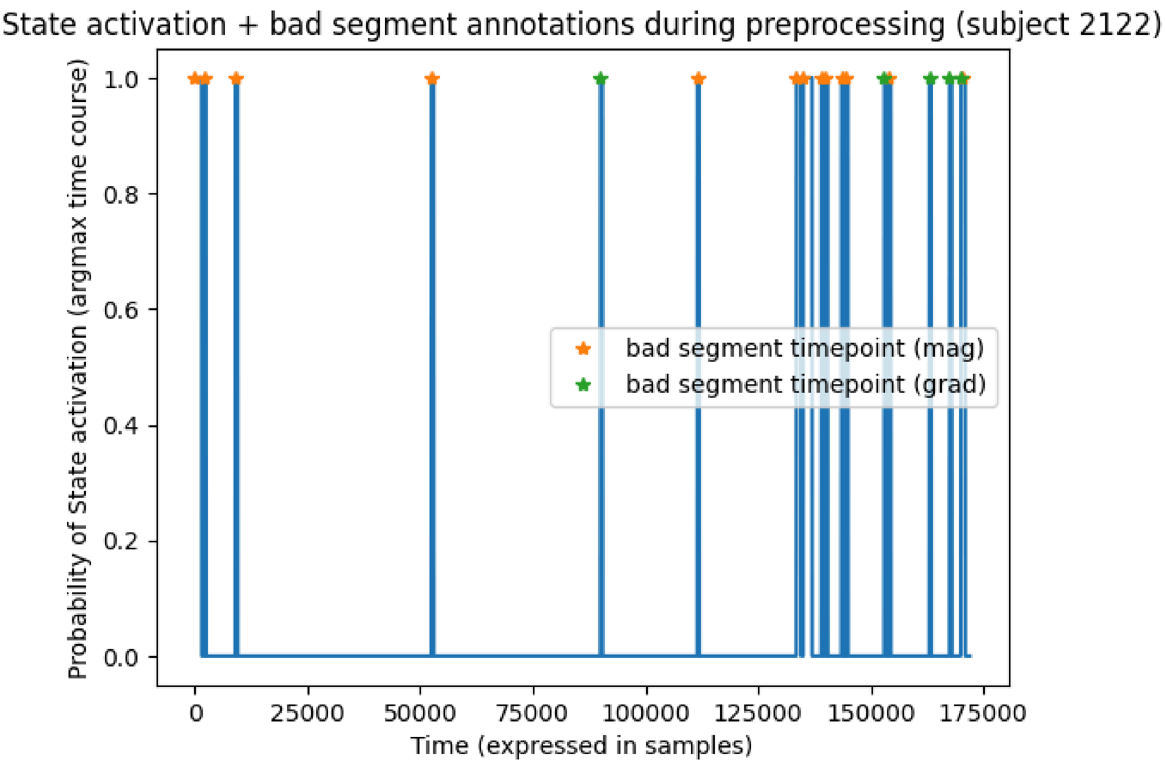

State activation + bad segment annotations during preprocessing (subject 1097)
Probability of State activation (argmax time course)
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000

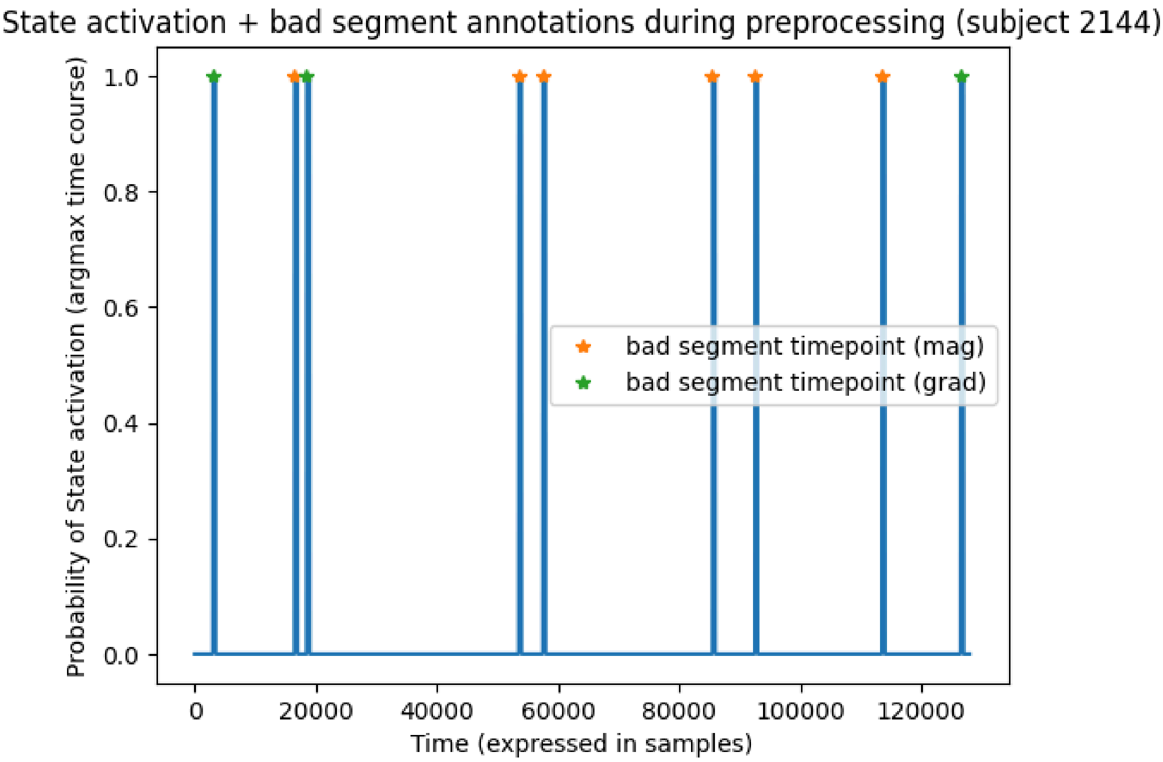

State activation + bad segment annotations during preprocessing (subject 1106)
Probability of State activation (argmax time course)
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)
1.0
0.8
0.6
0.4
0.2
0.0
0
50000
100000
150000
200000
250000
300000

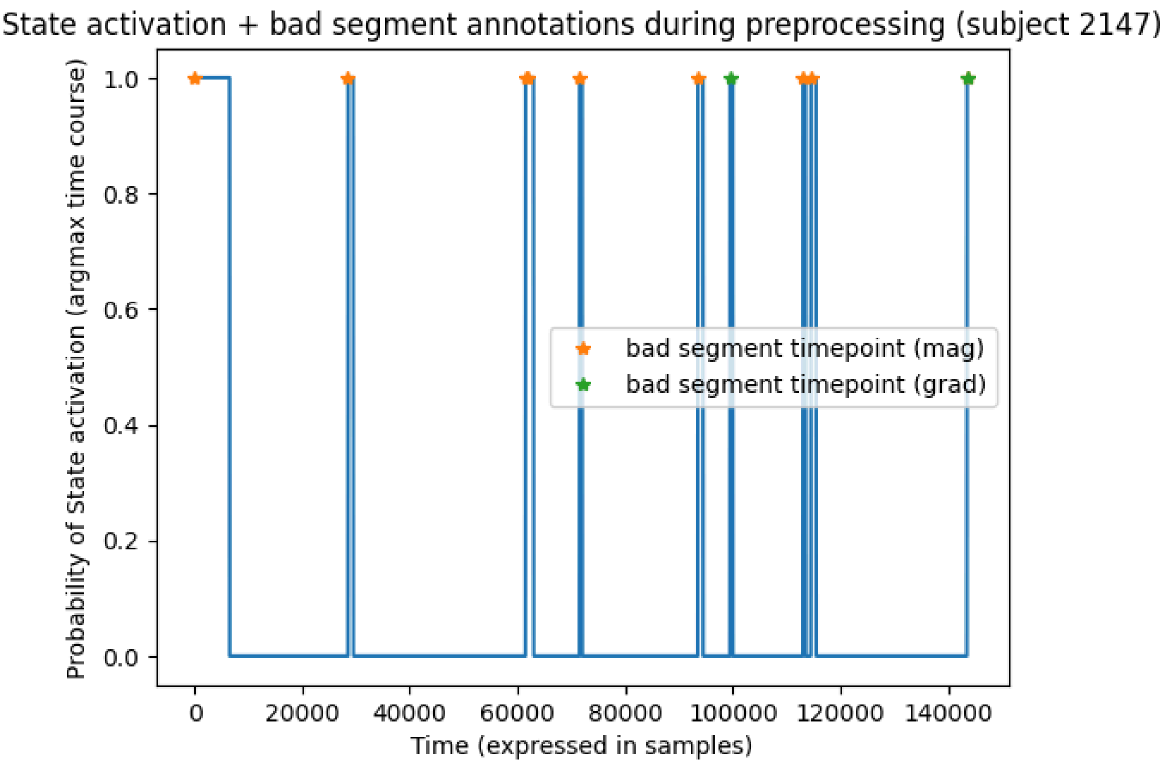

State activation + bad segment annotations during preprocessing (subject 2096)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)


State activation + bad segment annotations during preprocessing (subject 2102)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
140000
160000
Time (expressed in samples)

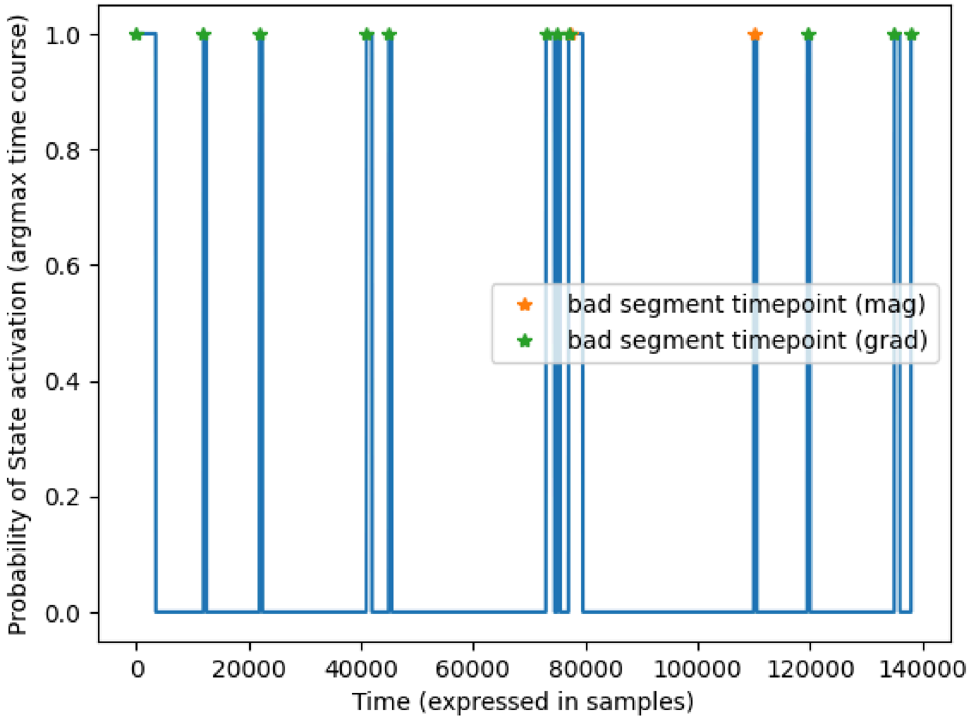

State activation + bad segment annotations during preprocessing (subject 2121)
Probability of State activation (argmax time course)
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)
1.0
0.8
0.6
0.4
0.2
0.0
0
25000
50000
75000
100000
125000
150000


State activation + bad segment annotations during preprocessing (subject 2122)
Probability of State activation (argmax time course)
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)
1.0
0.8
0.6
0.4
0.2
0.0
0
25000
50000
75000
100000
125000
150000
175000

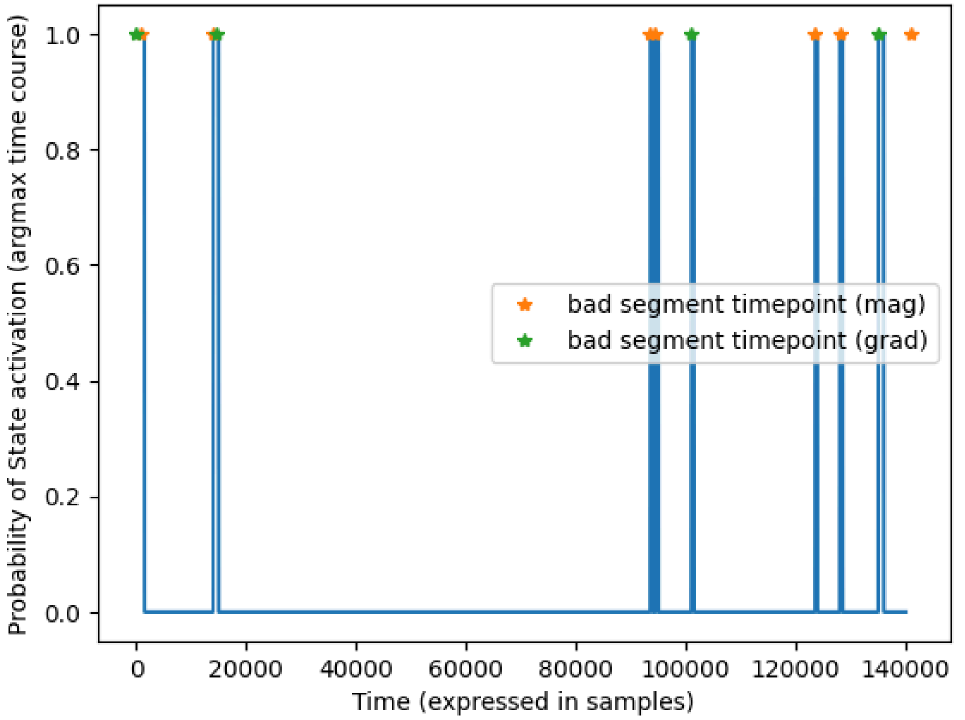

State activation + bad segment annotations during preprocessing (subject 2144)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

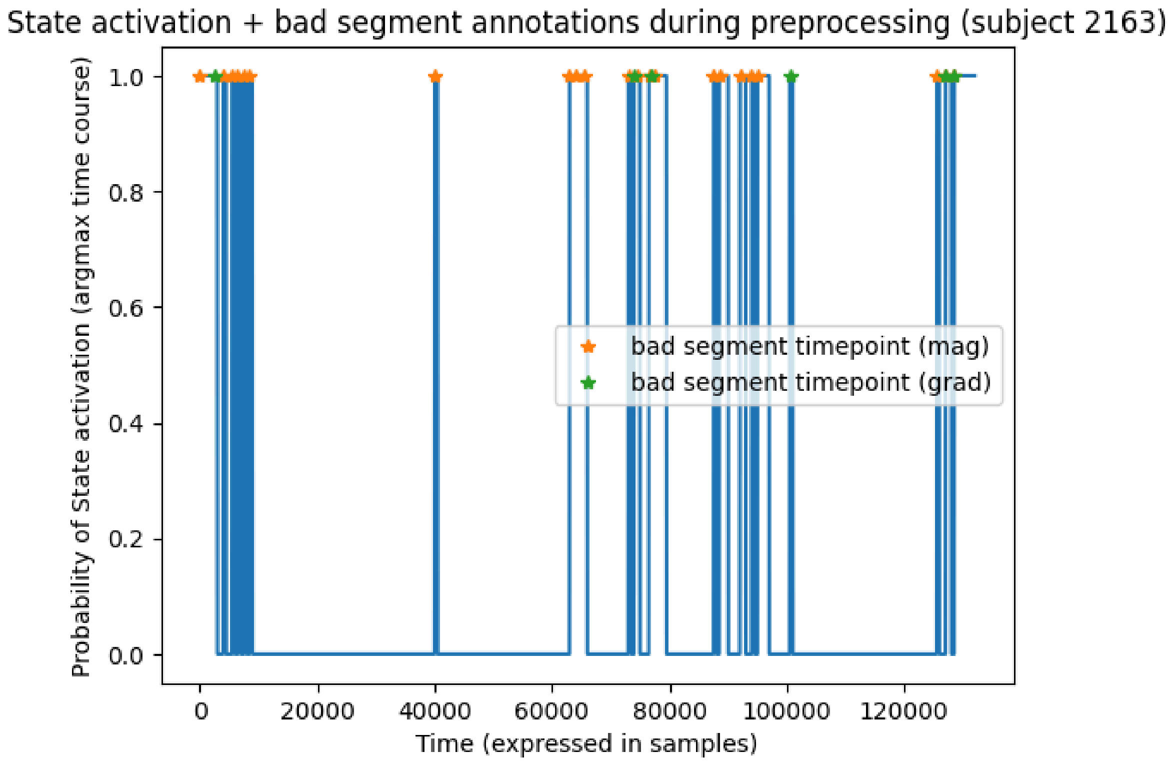

State activation + bad segment annotations during preprocessing (subject 2147)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

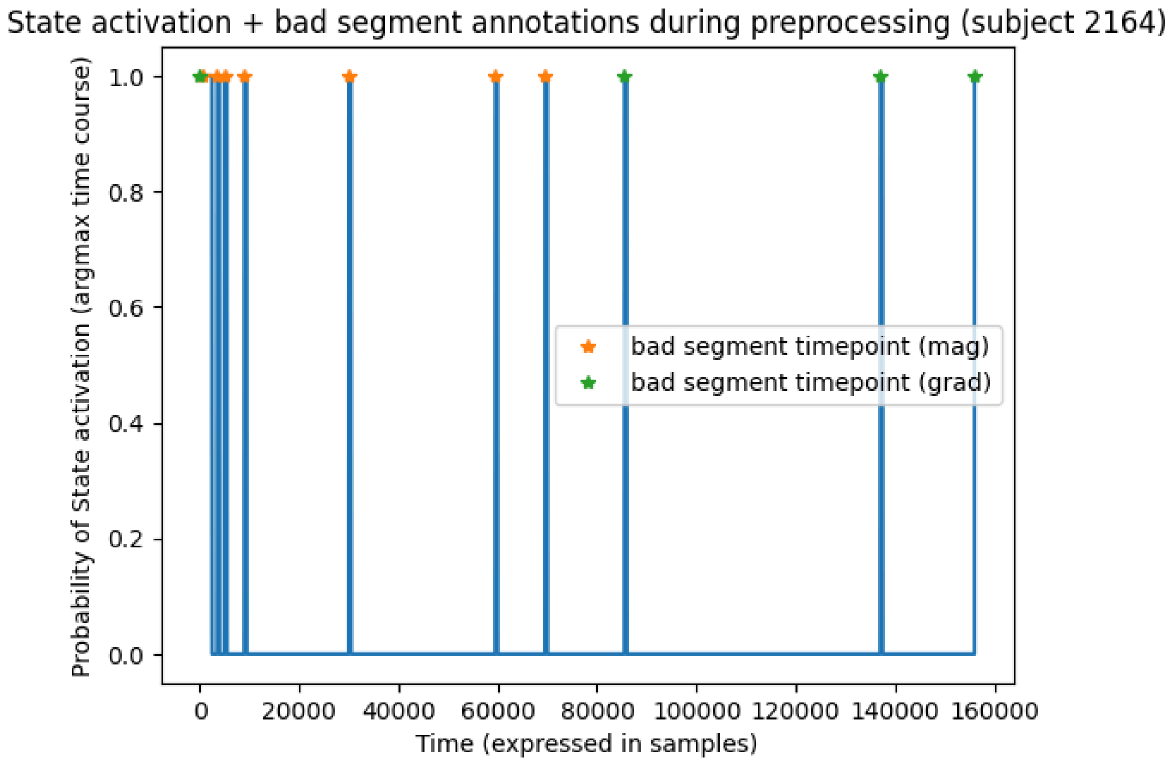
State activation + bad segment annotations during preprocessing (subject 2150)

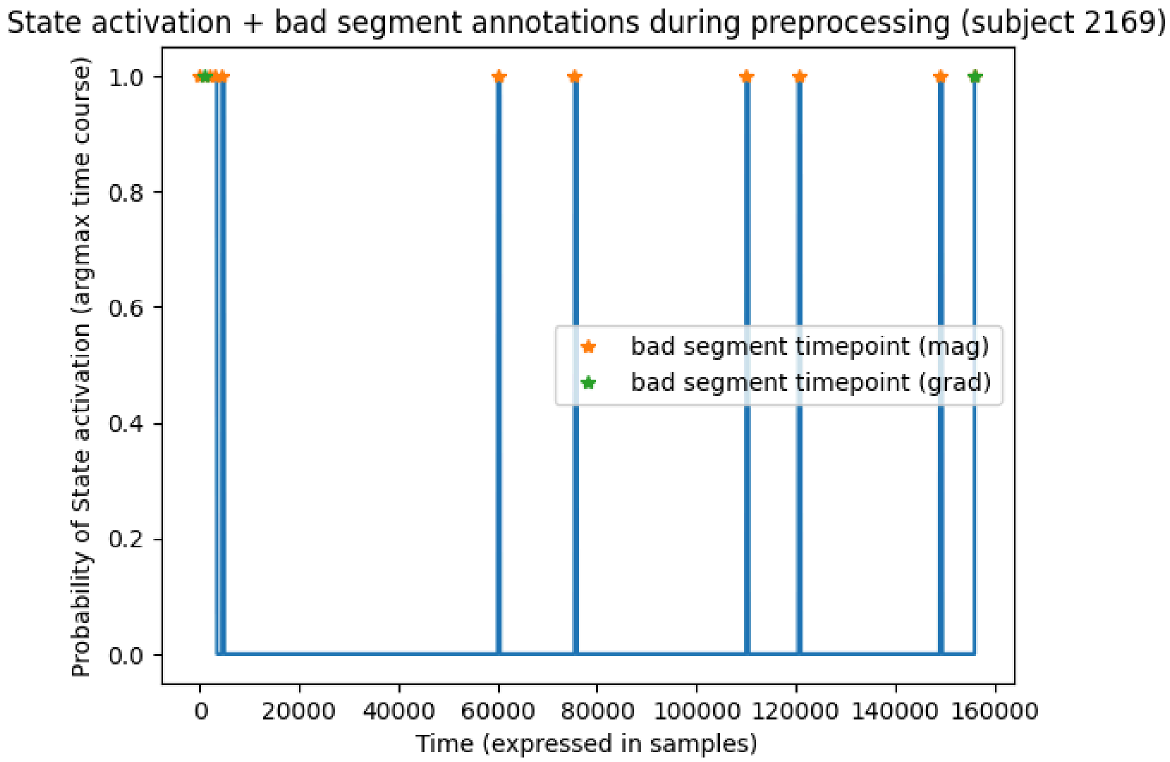


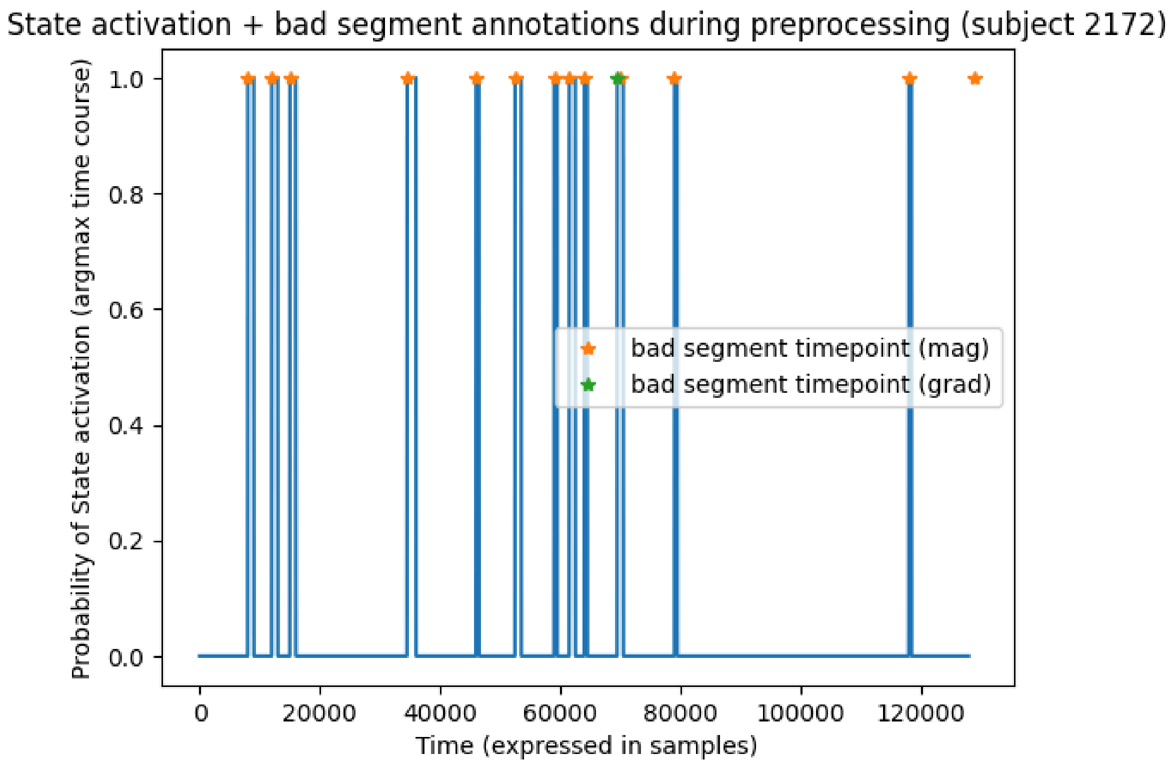
State activation + bad segment annotations during preprocessing (subject 2151)

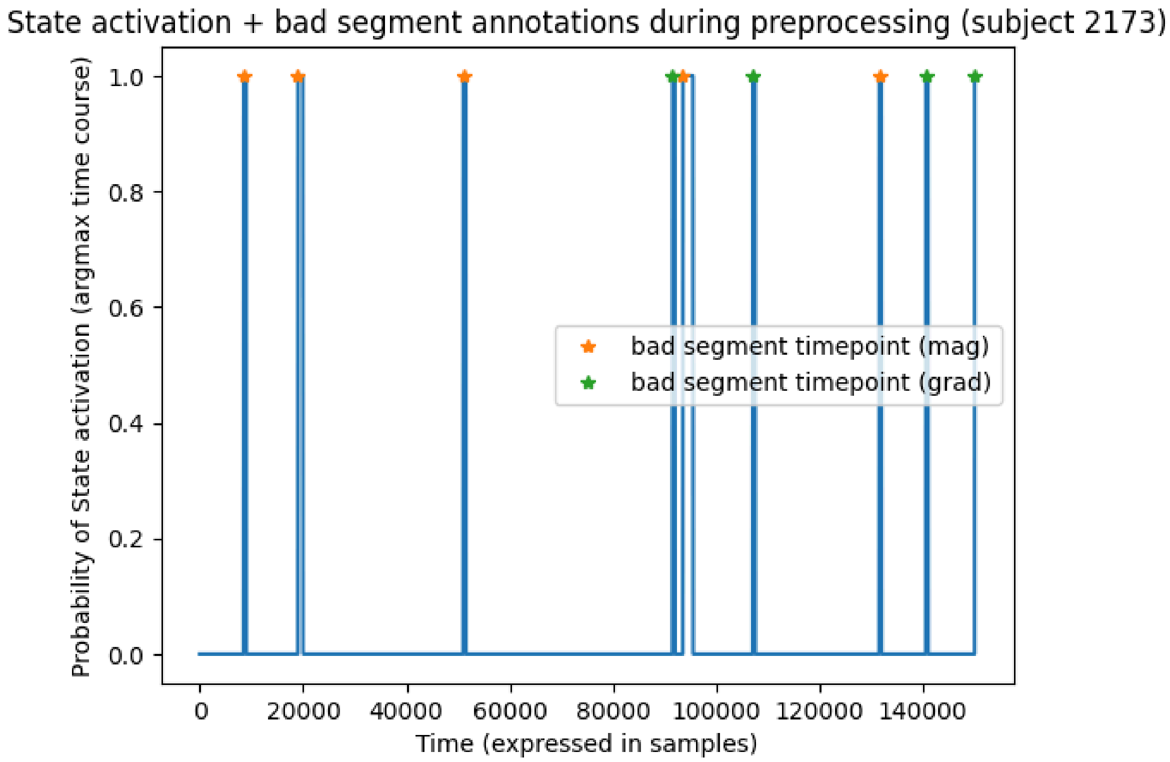


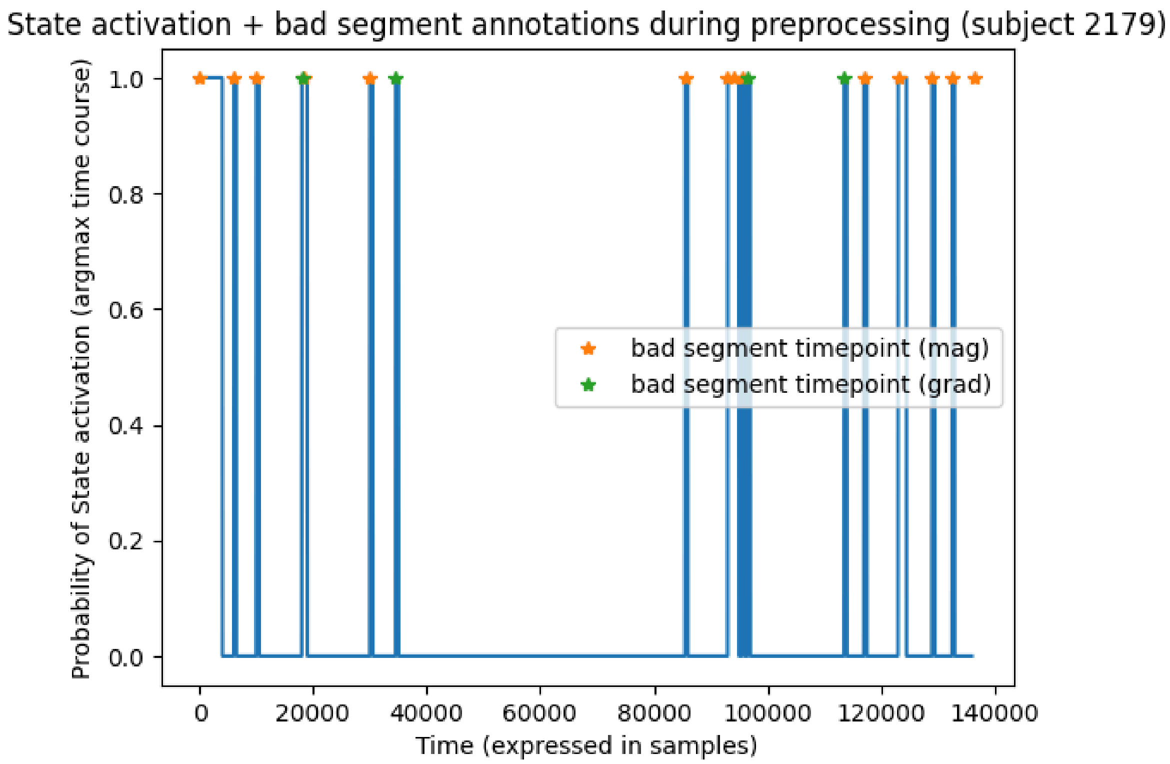

State activation + bad segment annotations during preprocessing (subject 2163)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

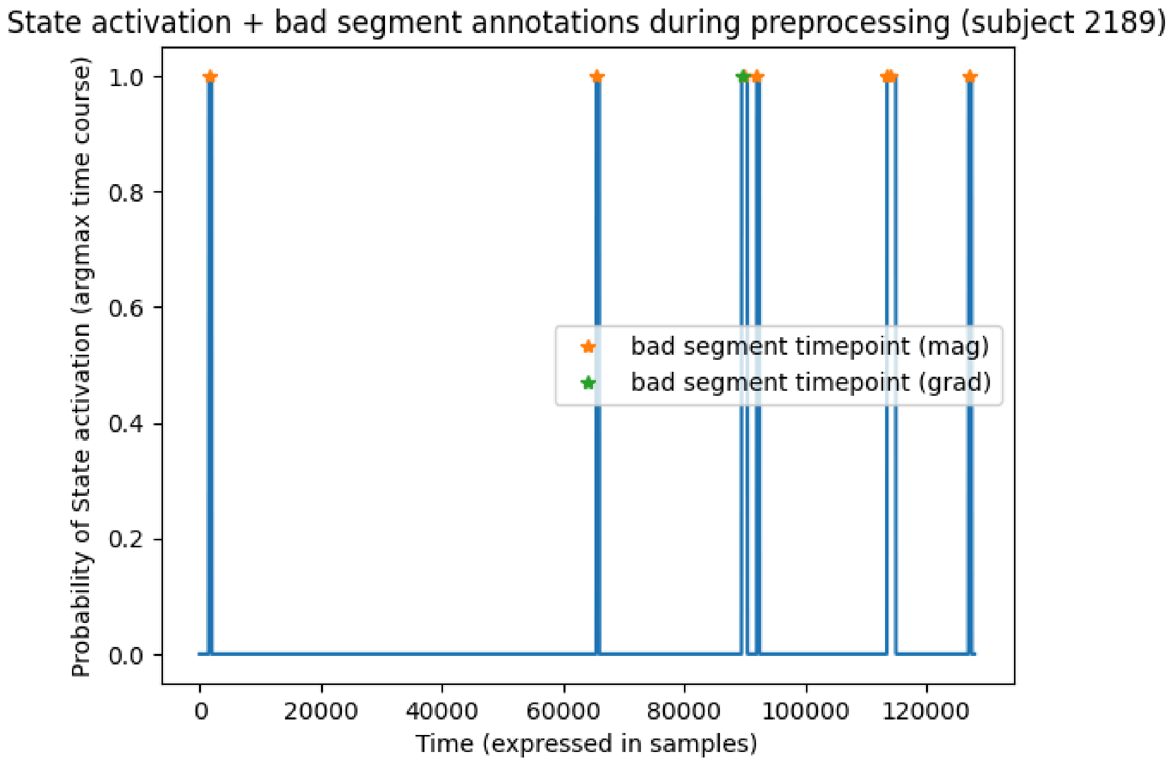

State activation + bad segment annotations during preprocessing (subject 2164)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
160000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

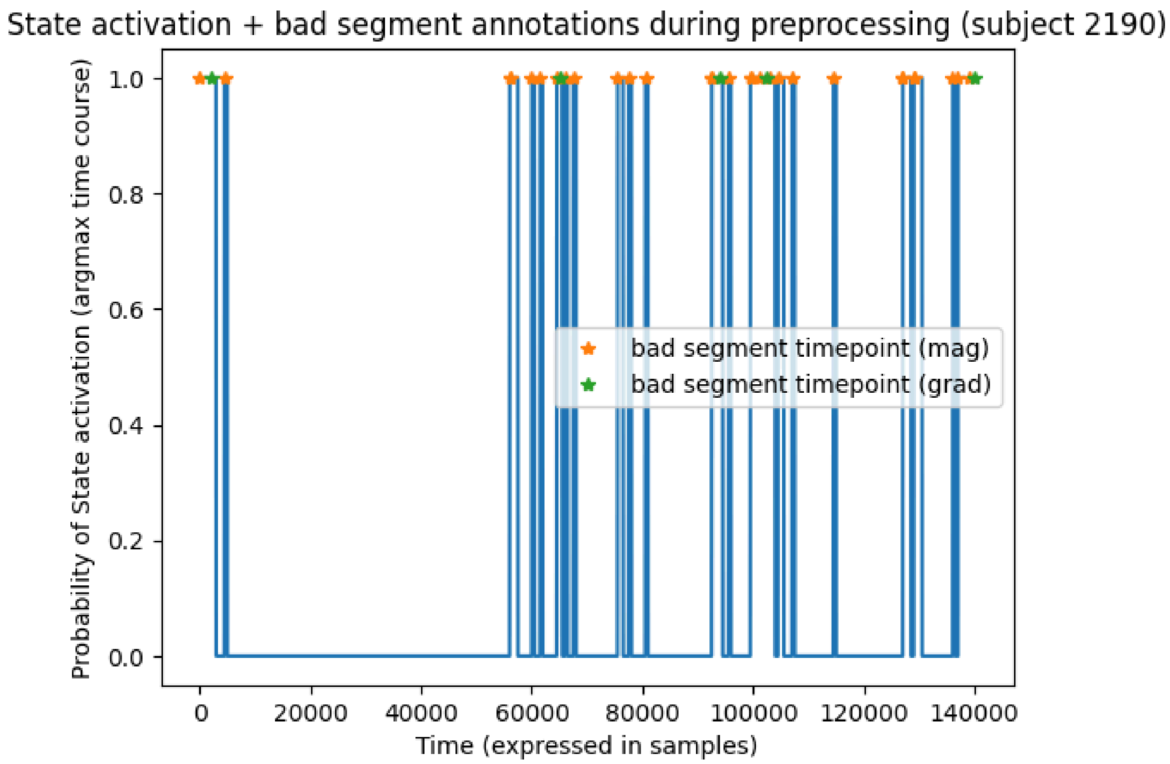

State activation + bad segment annotations during preprocessing (subject 2169)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
140000
160000
Time (expressed in samples)

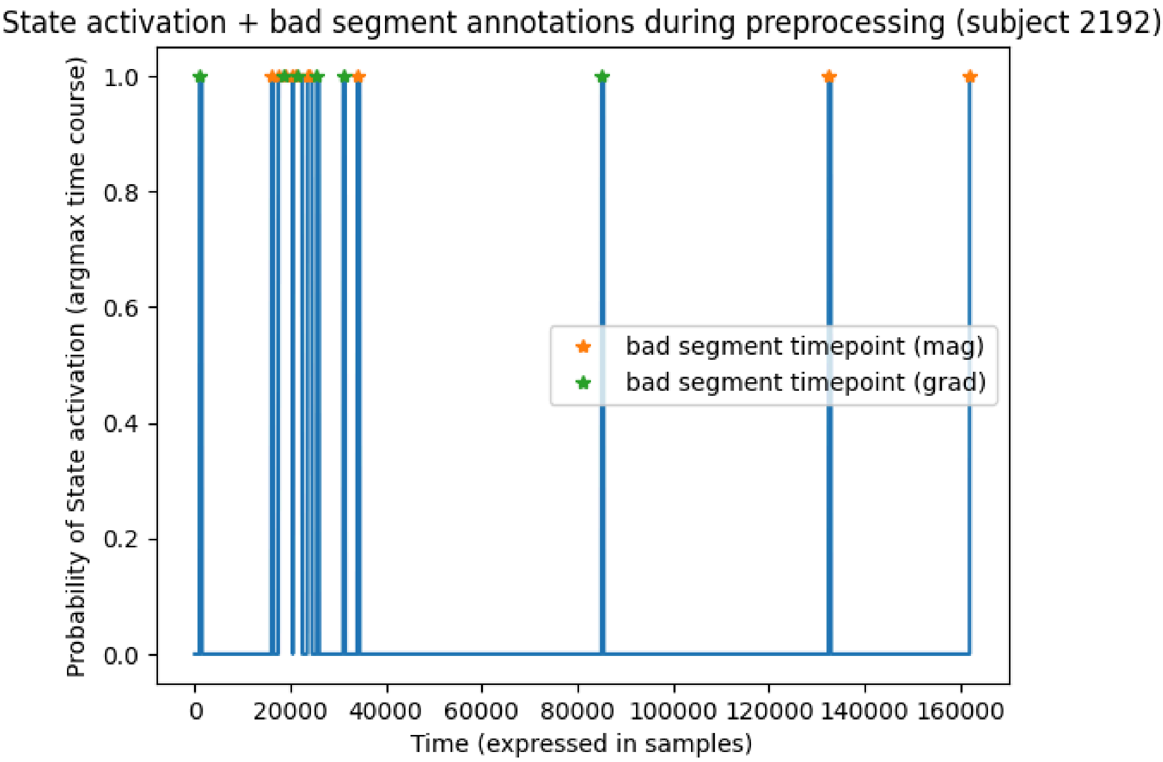

State activation + bad segment annotations during preprocessing (subject 2172)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)

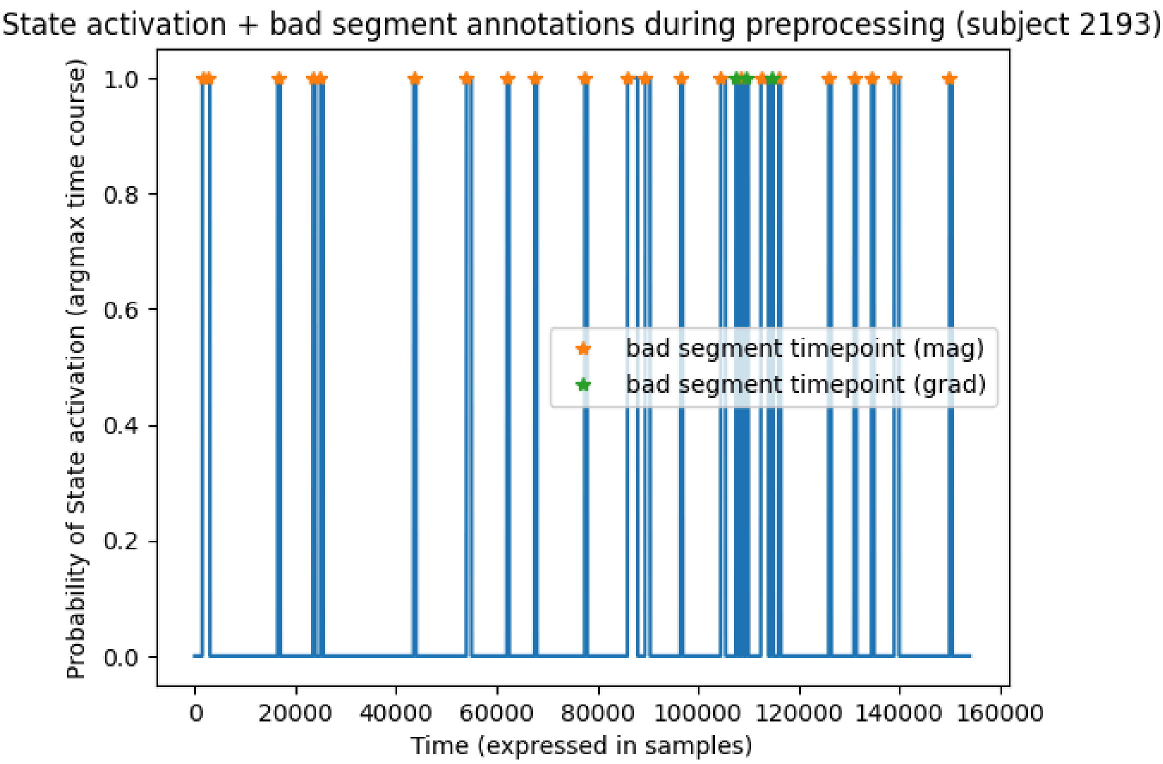

State activation + bad segment annotations during preprocessing (subject 2173)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)

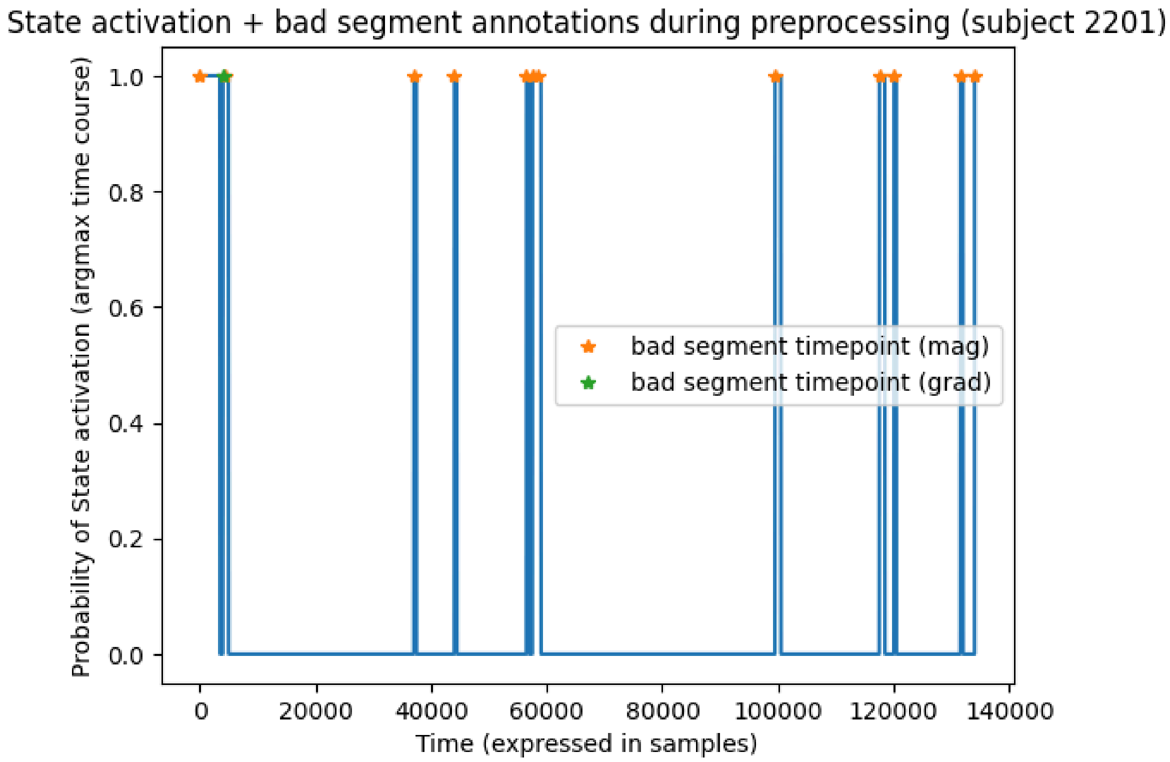

State activation + bad segment annotations during preprocessing (subject 2179)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)

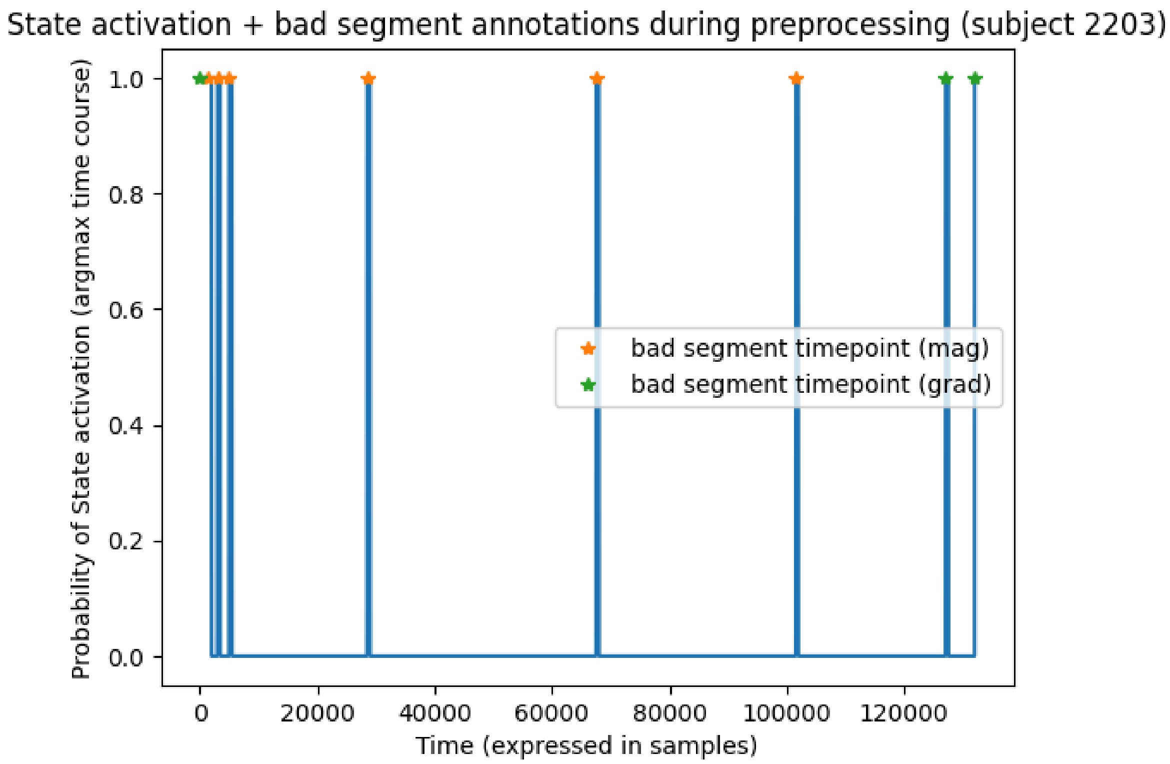

State activation + bad segment annotations during preprocessing (subject 2189)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

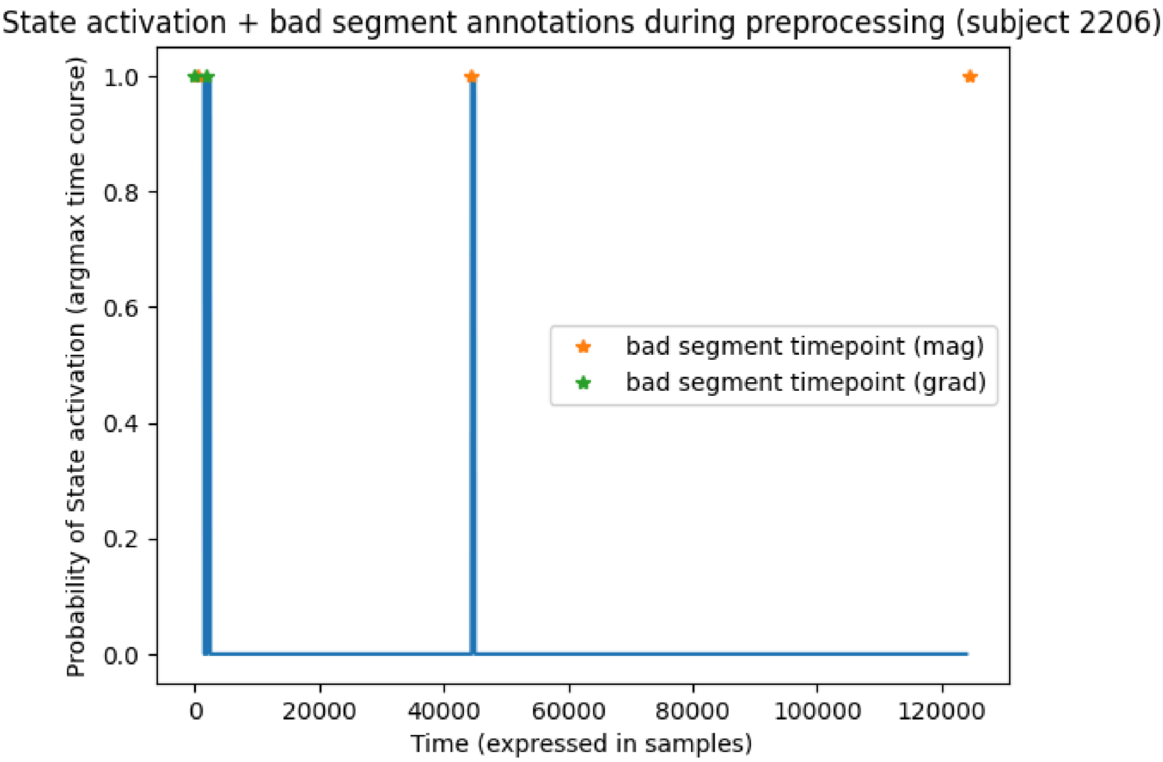

State activation + bad segment annotations during preprocessing (subject 2190)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

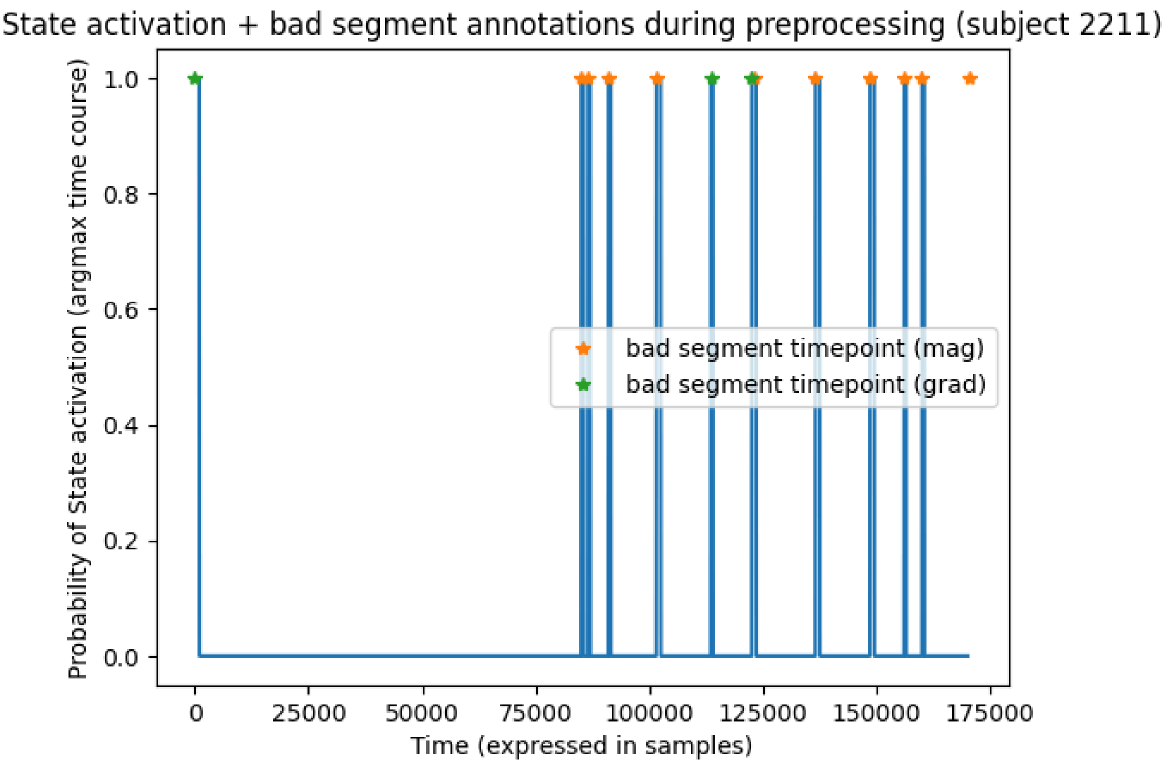

State activation + bad segment annotations during preprocessing (subject 2192)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
160000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

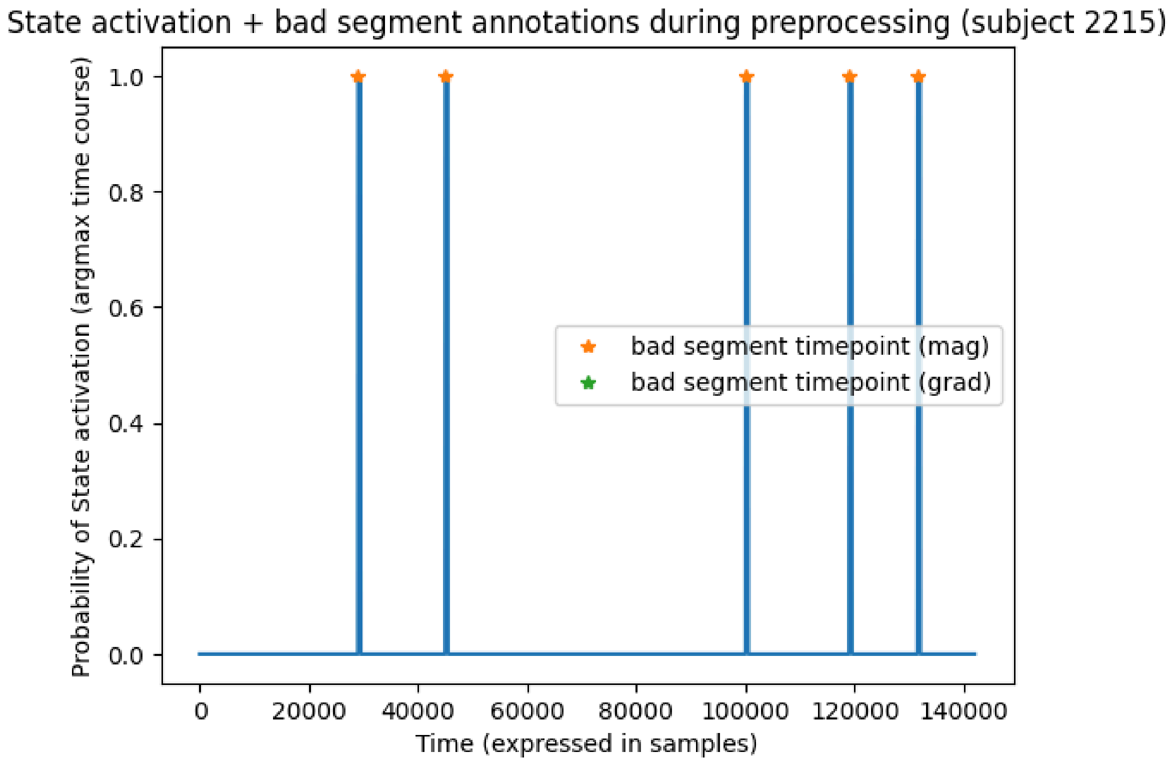

State activation + bad segment annotations during preprocessing (subject 2193)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
160000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

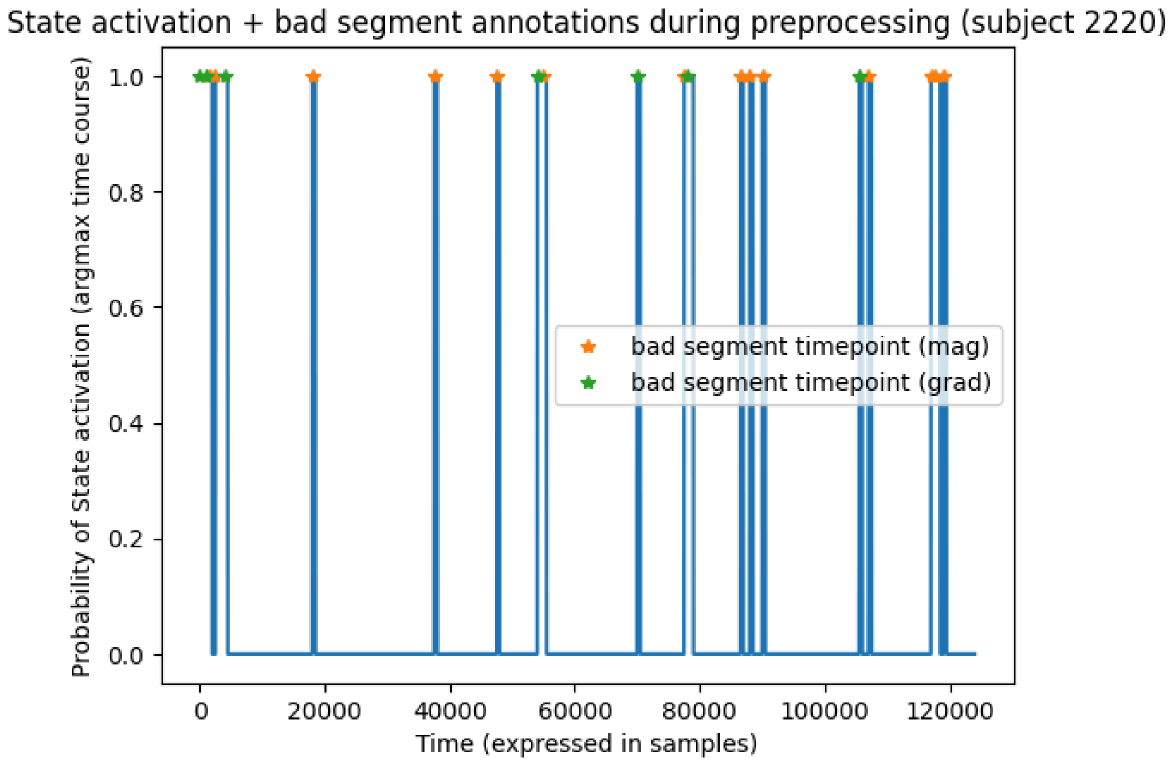

State activation + bad segment annotations during preprocessing (subject 2201)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

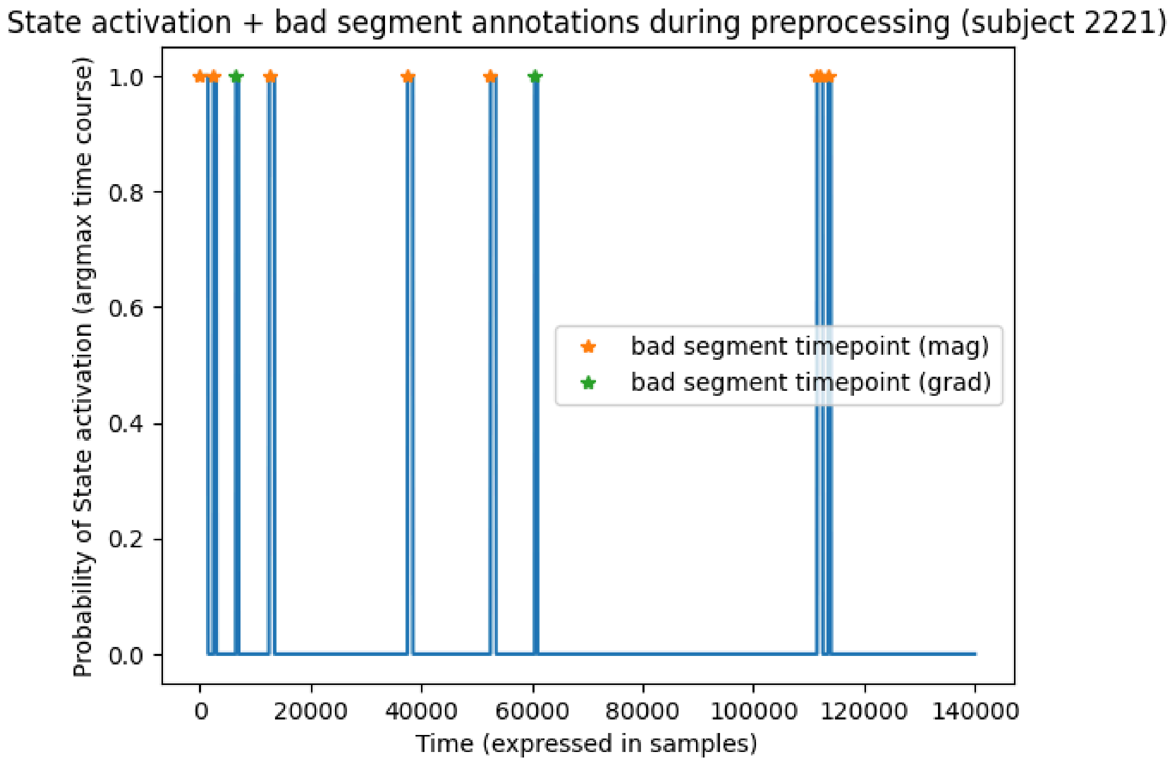

State activation + bad segment annotations during preprocessing (subject 2203)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

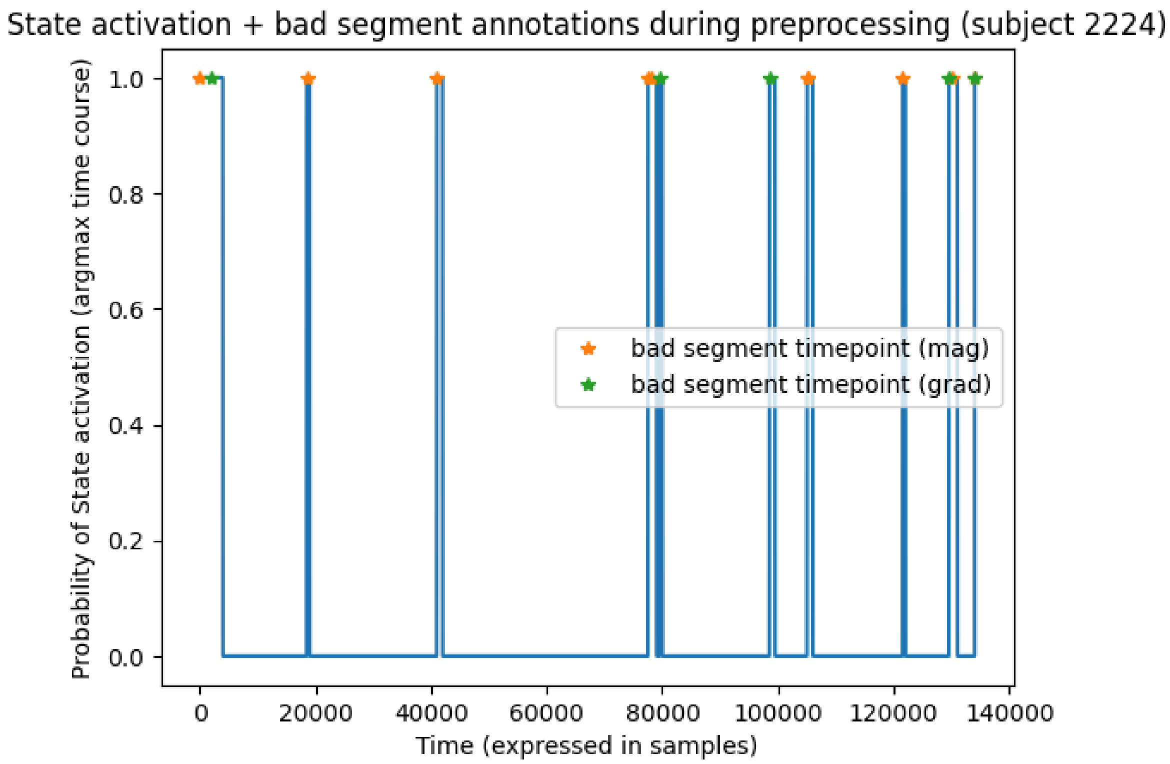

State activation + bad segment annotations during preprocessing (subject 2206)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

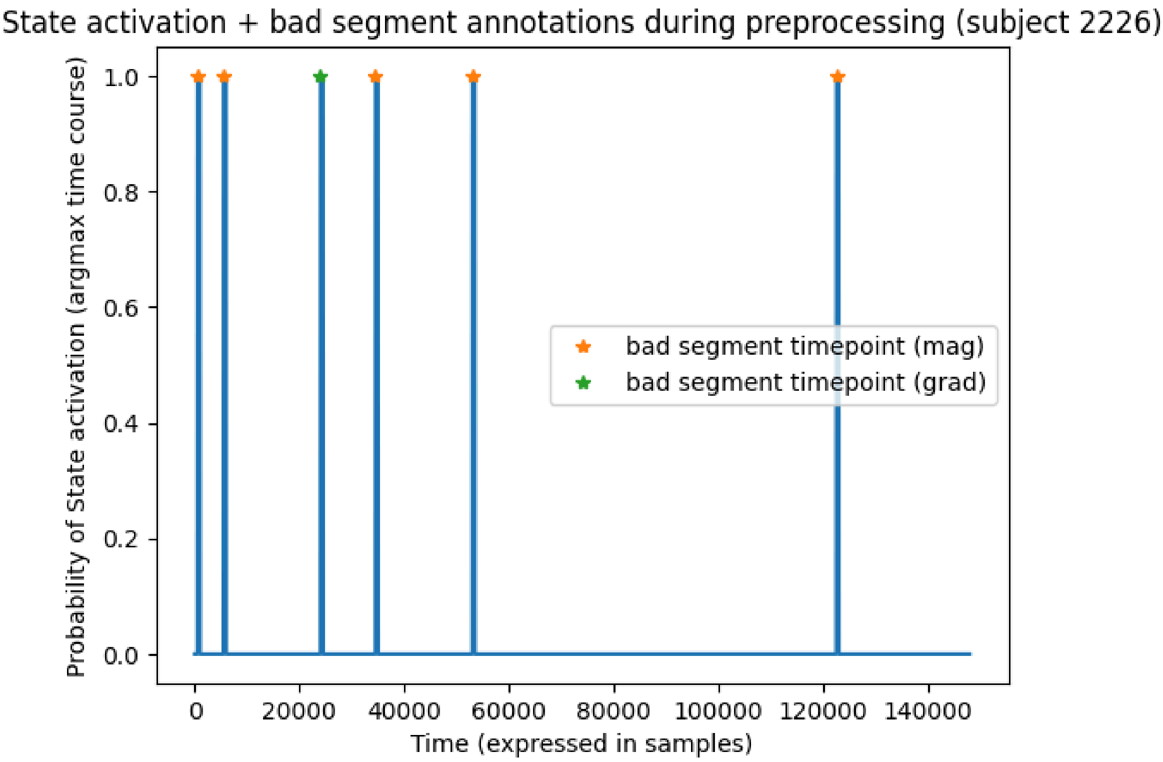

State activation + bad segment annotations during preprocessing (subject 2211)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
25000
50000
75000
100000
125000
150000
175000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

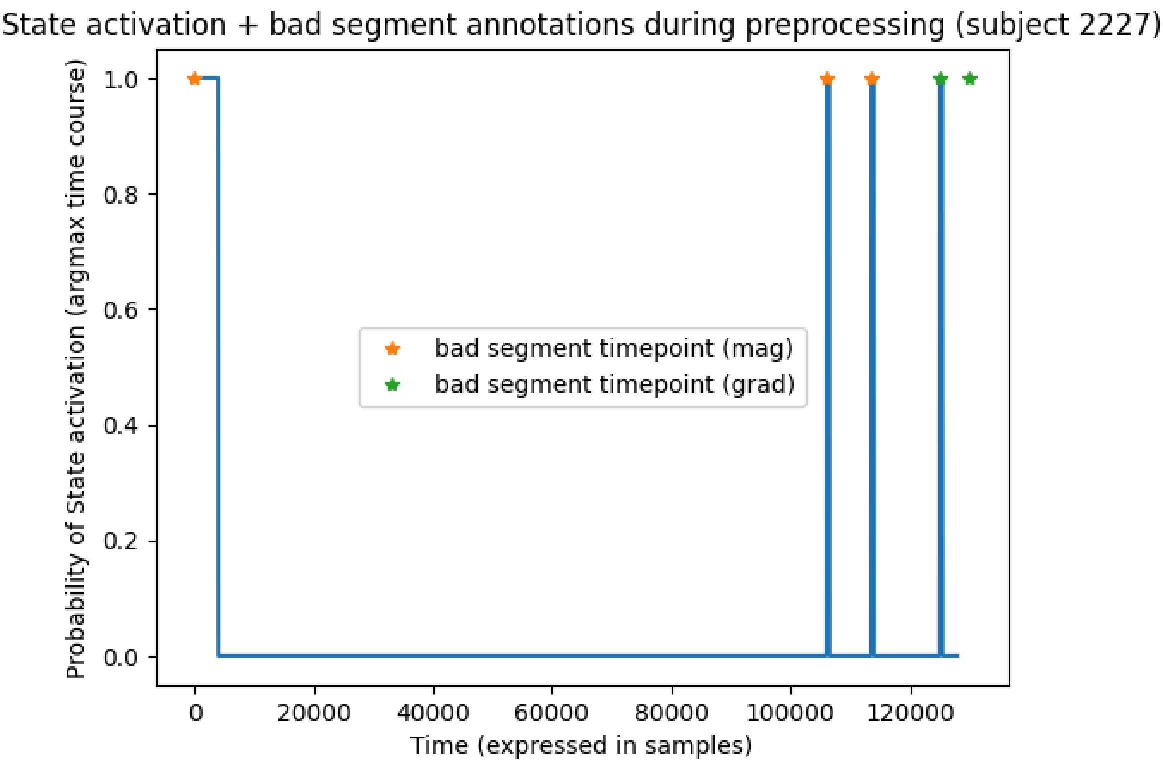

State activation + bad segment annotations during preprocessing (subject 2215)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)

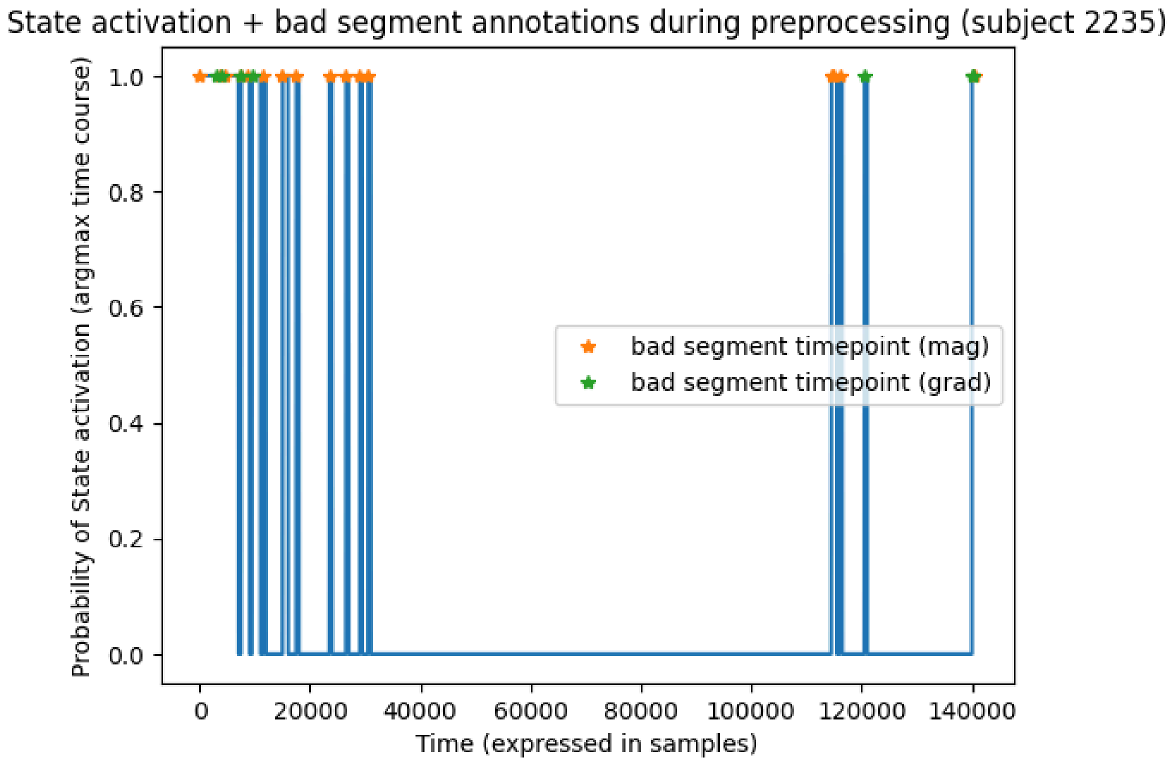

State activation + bad segment annotations during preprocessing (subject 2220)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)

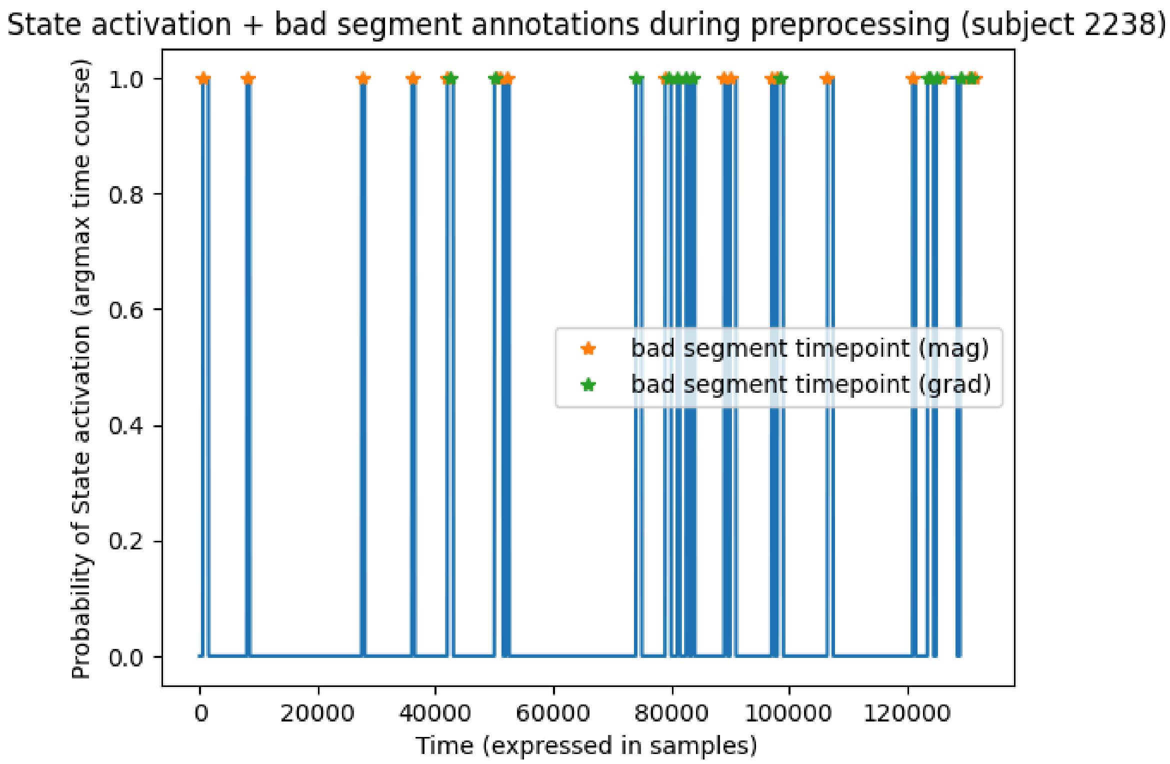

State activation + bad segment annotations during preprocessing (subject 2221)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

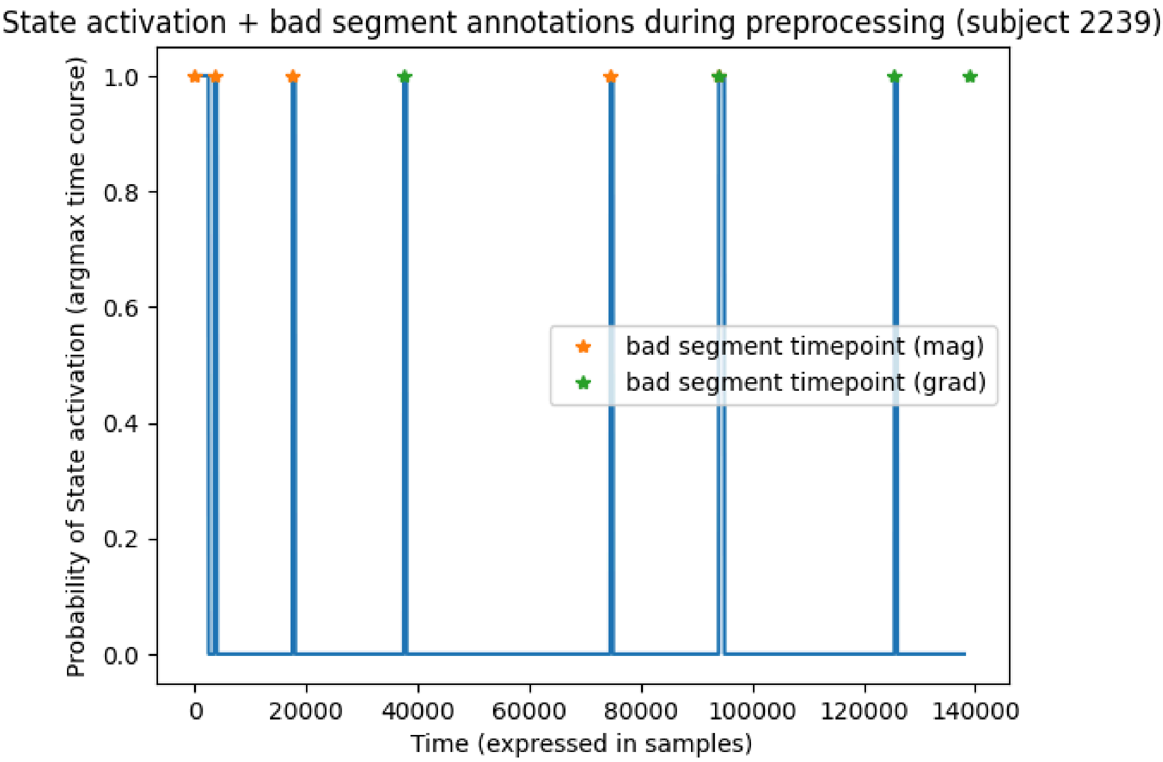

State activation + bad segment annotations during preprocessing (subject 2224)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

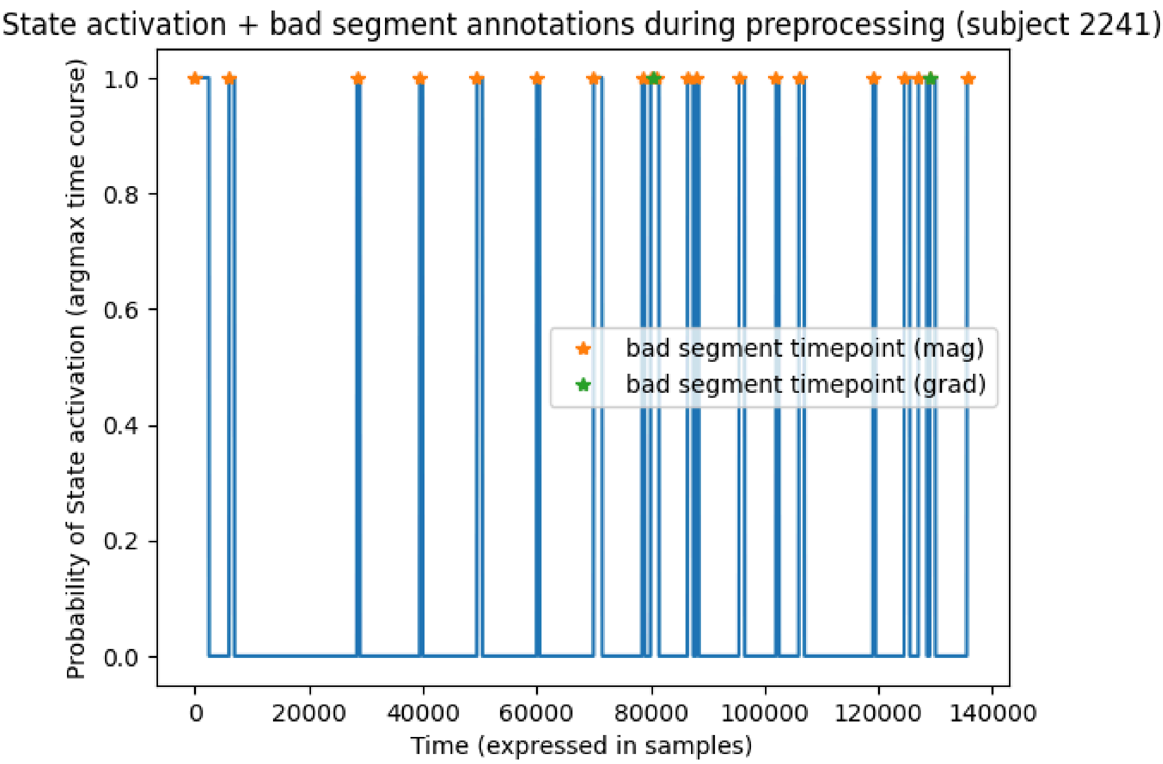

State activation + bad segment annotations during preprocessing (subject 2226)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

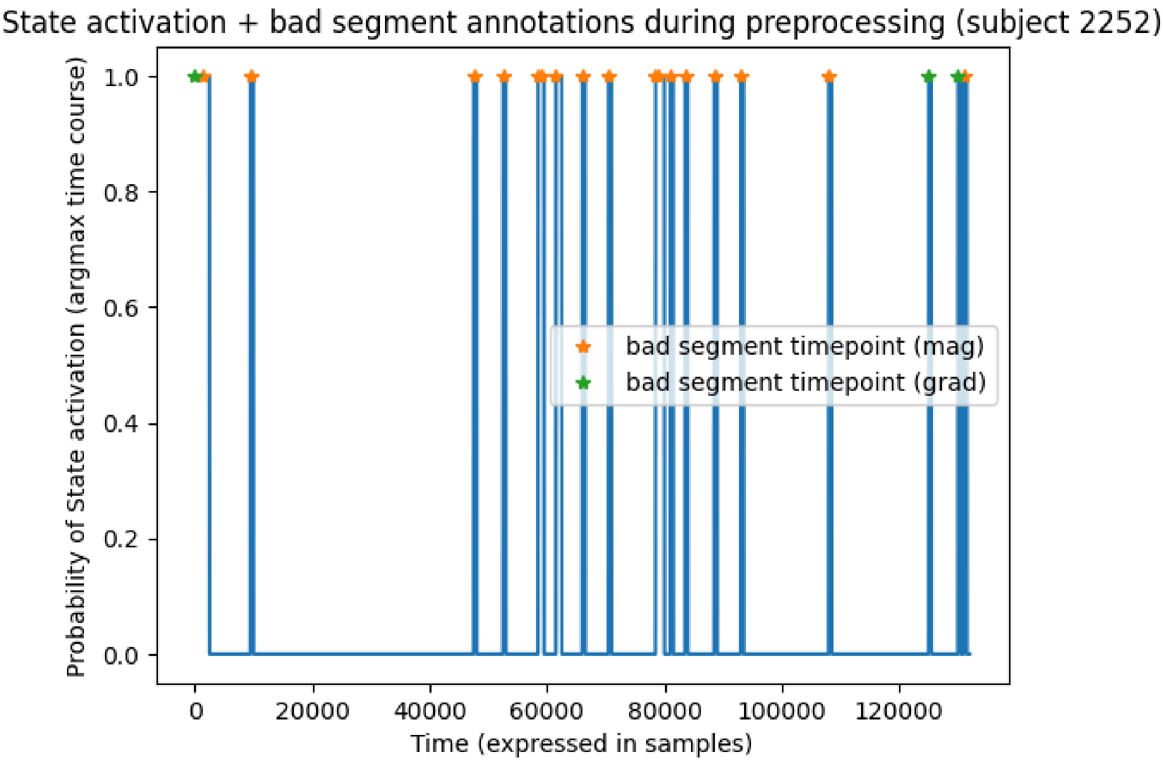

State activation + bad segment annotations during preprocessing (subject 2227)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

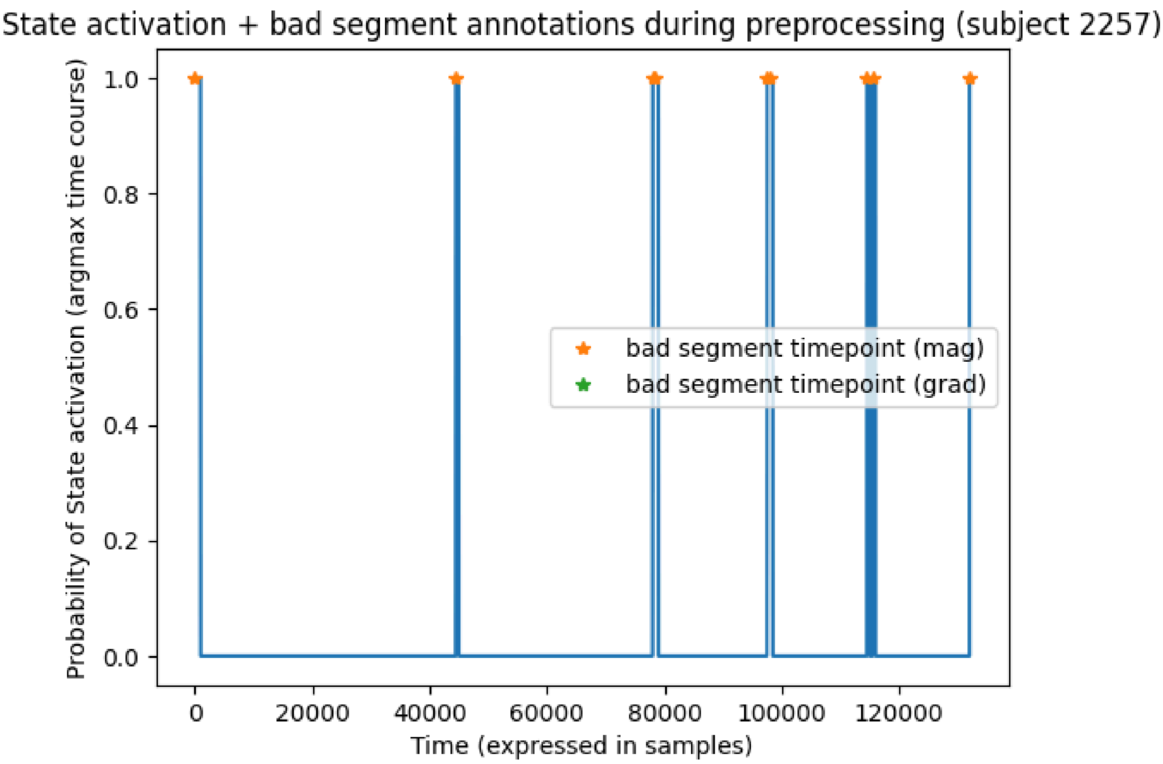

State activation + bad segment annotations during preprocessing (subject 2235)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)


State activation + bad segment annotations during preprocessing (subject 2238)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

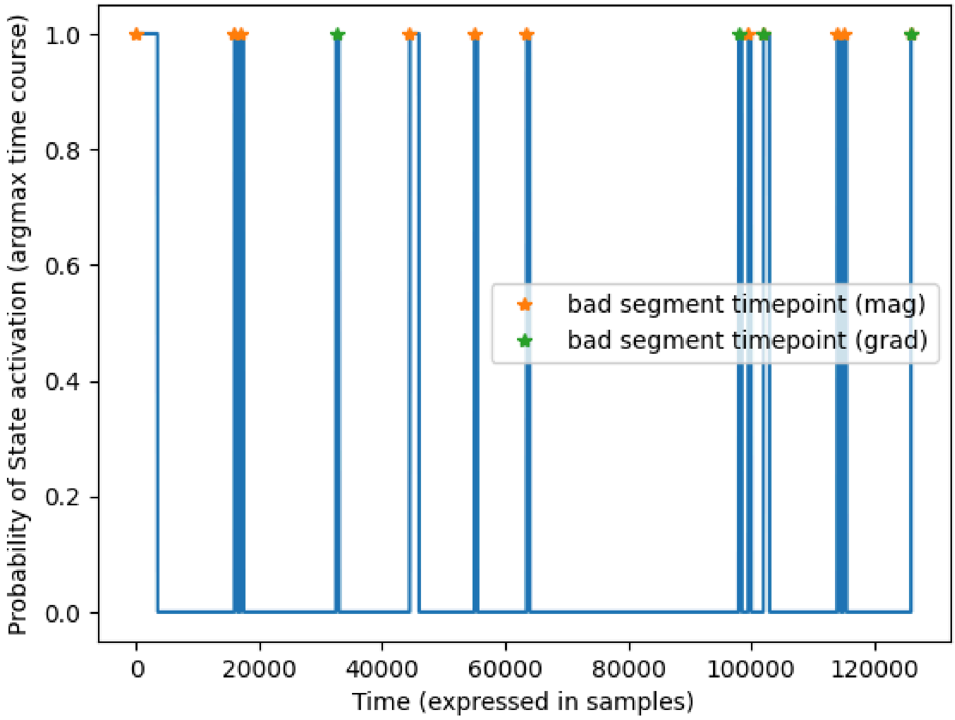

State activation + bad segment annotations during preprocessing (subject 2239)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)


State activation + bad segment annotations during preprocessing (subject 2241)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

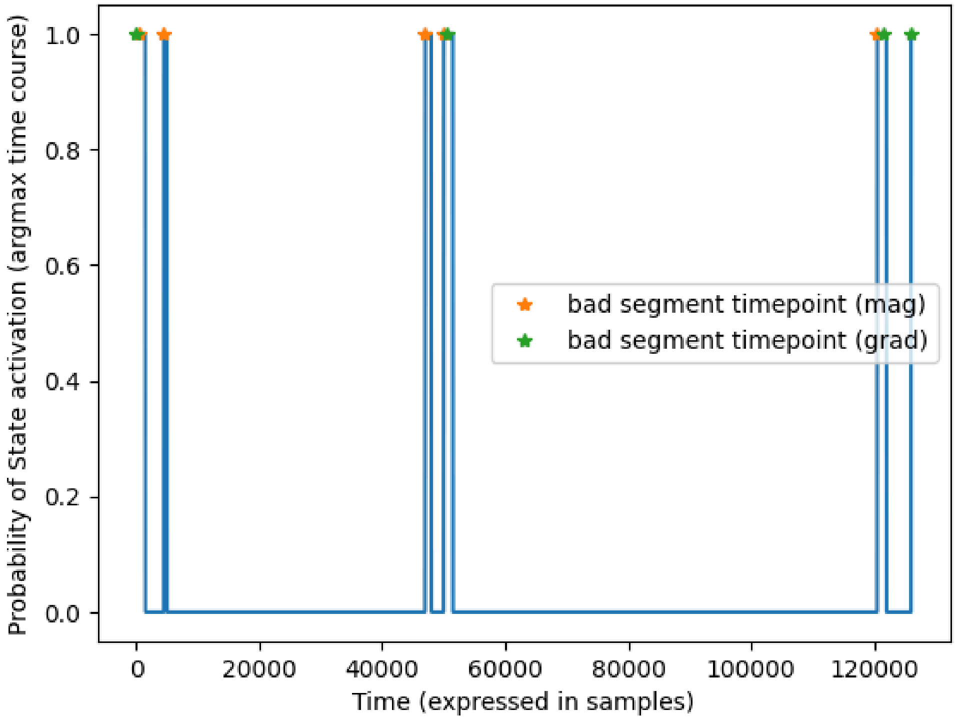

State activation + bad segment annotations during preprocessing (subject 2252)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)


State activation + bad segment annotations during preprocessing (subject 2257)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

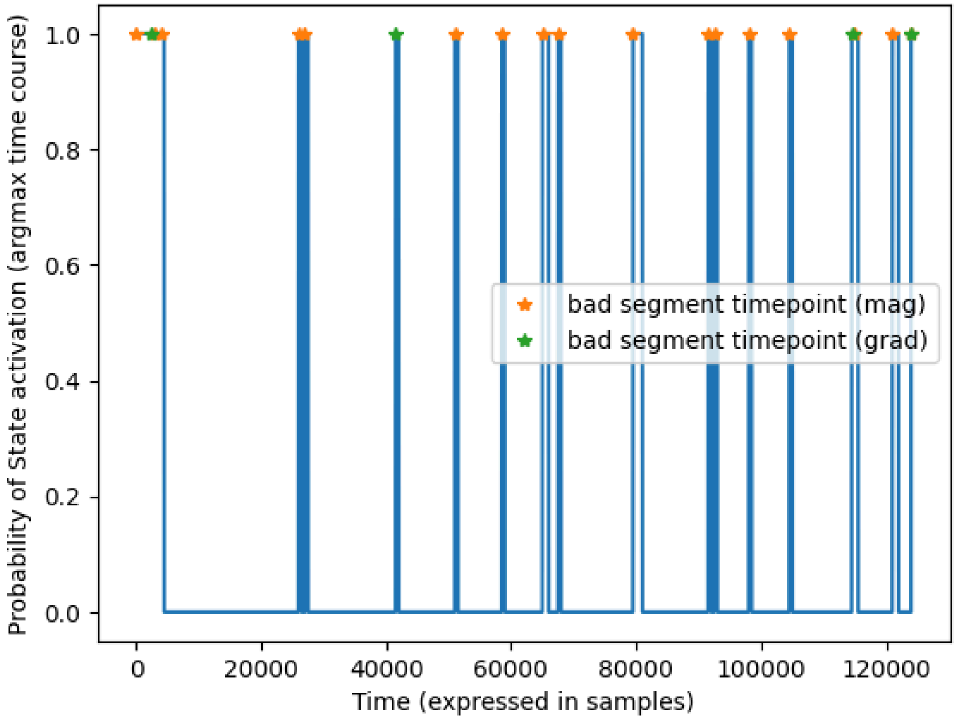
State activation + bad segment annotations during preprocessing (subject 2264)



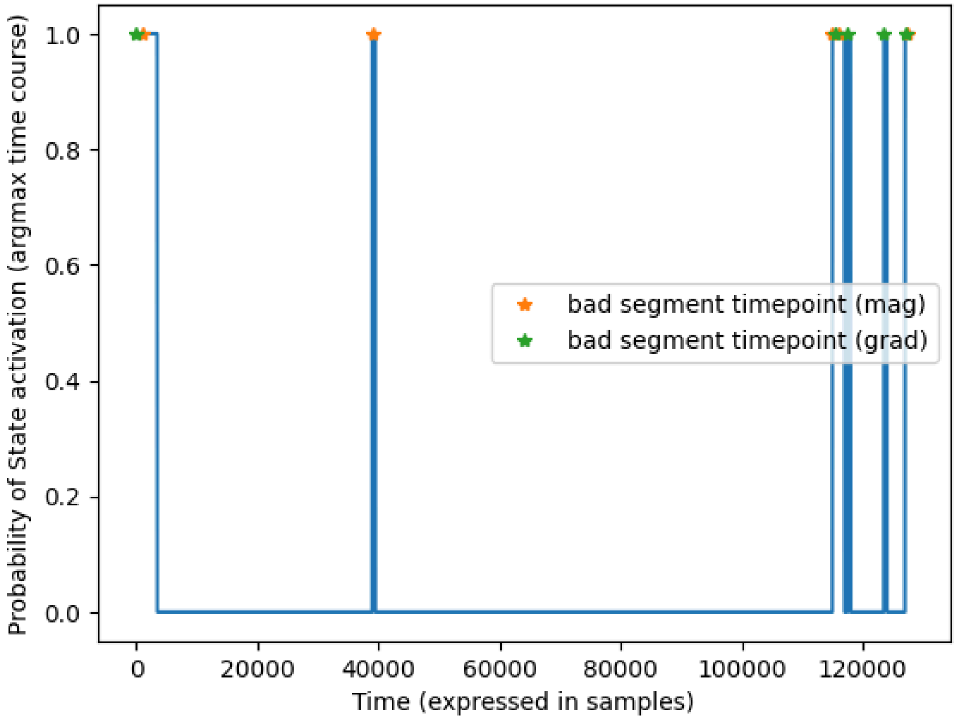
State activation + bad segment annotations during preprocessing (subject 2266)

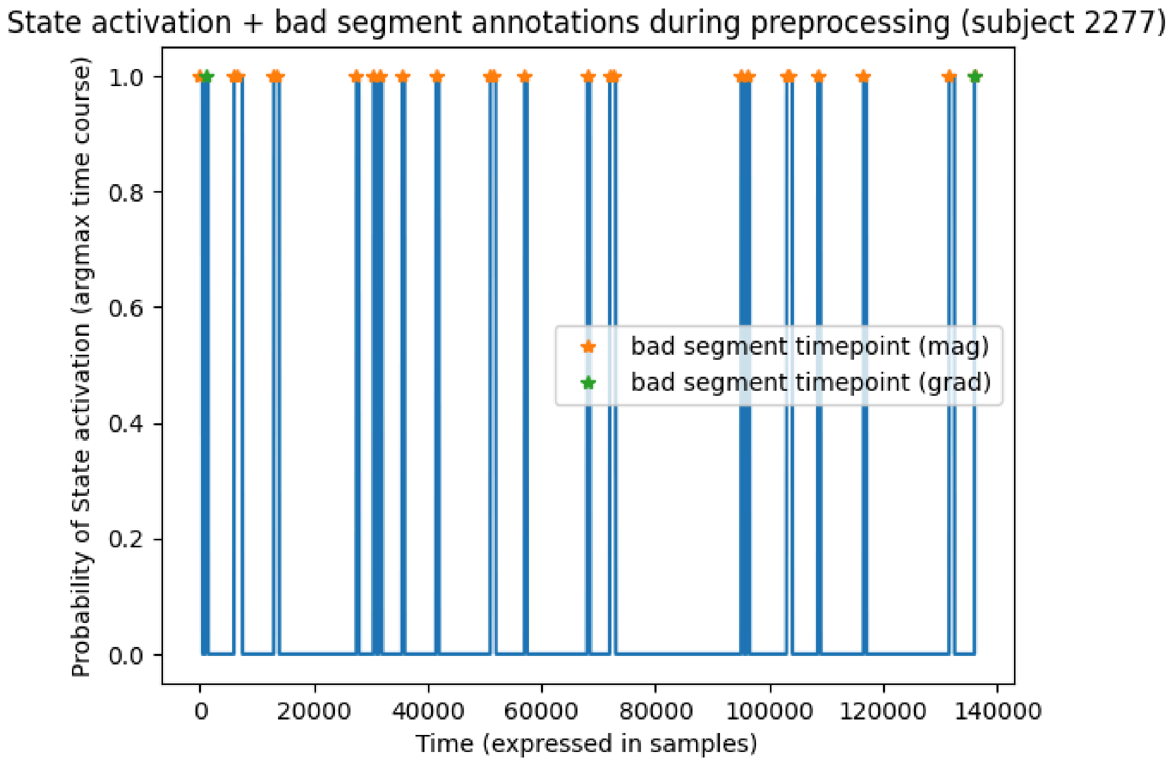


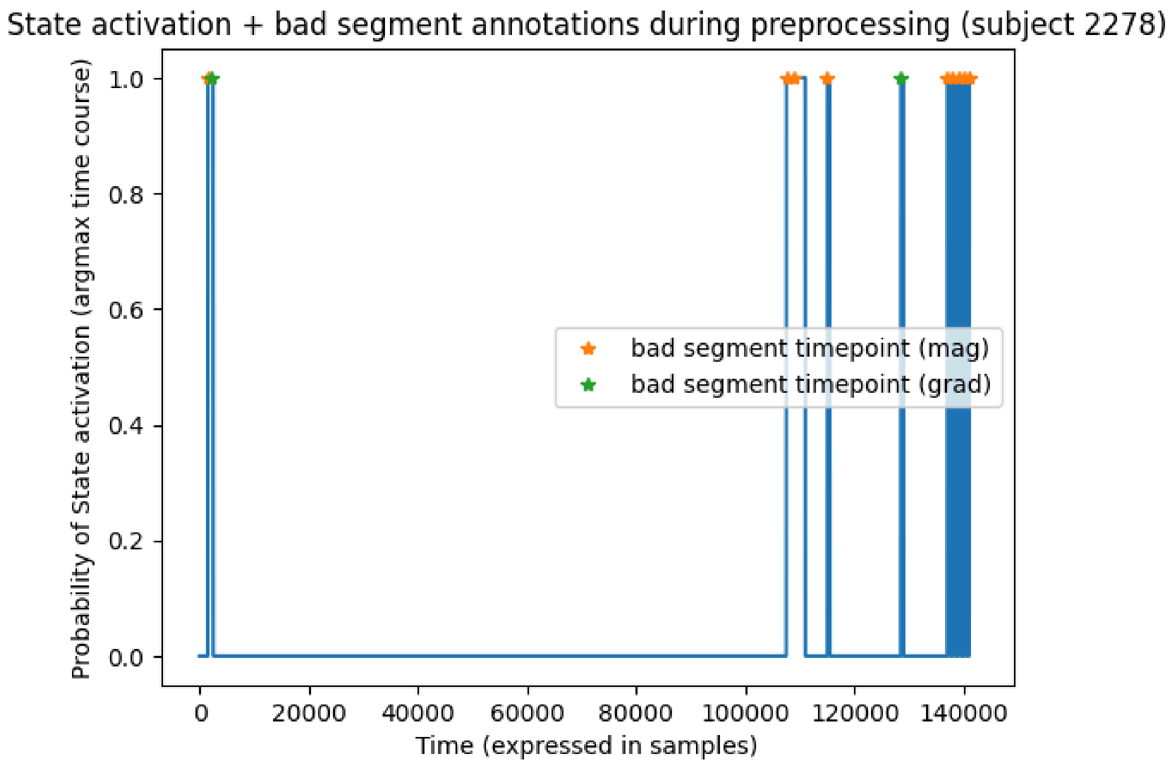
State activation + bad segment annotations during preprocessing (subject 2267)



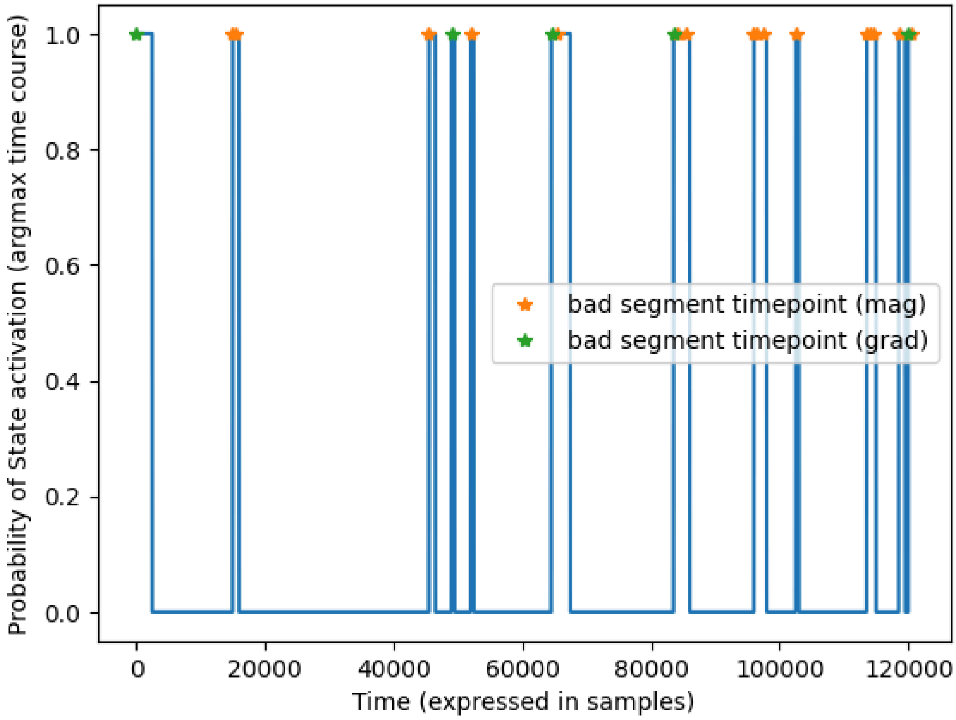
State activation + bad segment annotations during preprocessing (subject 2268)



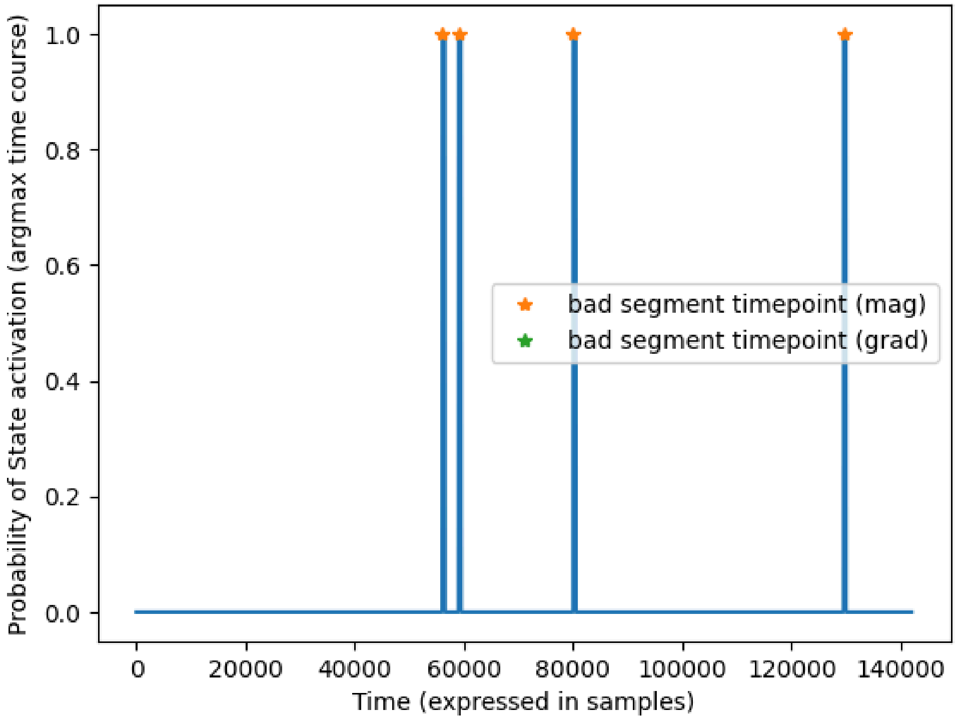

State activation + bad segment annotations during preprocessing (subject 2277)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)

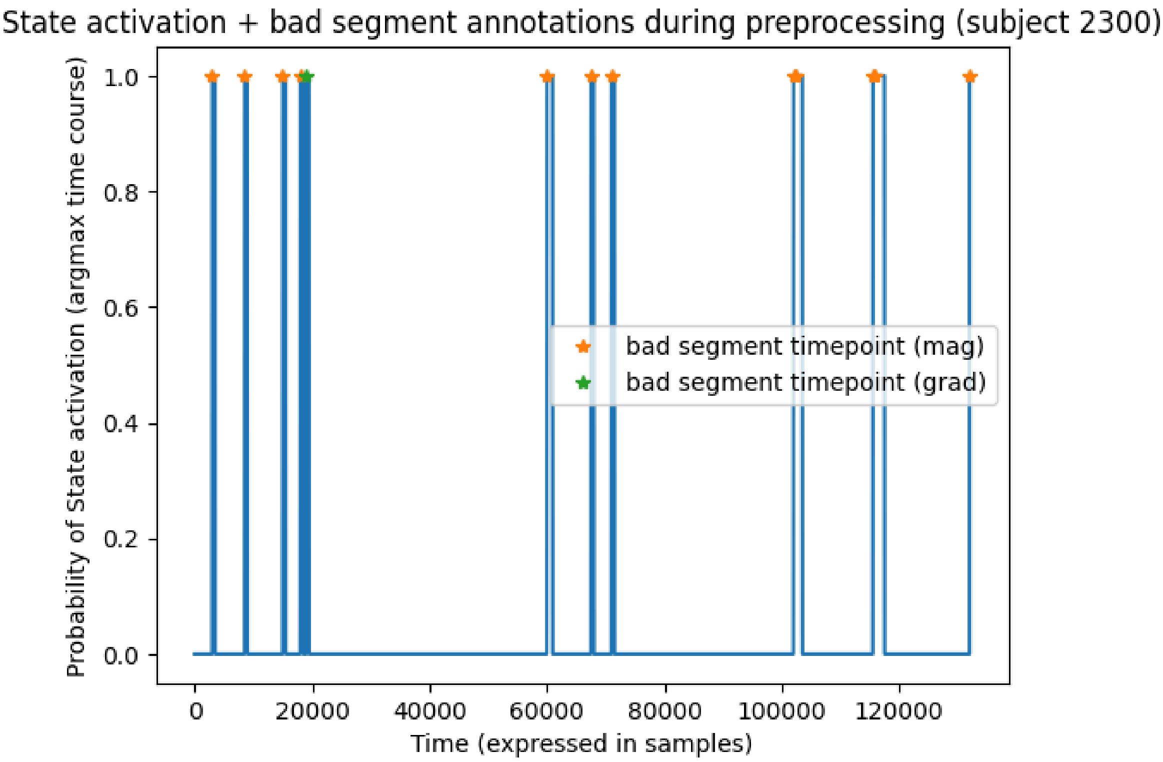

State activation + bad segment annotations during preprocessing (subject 2278)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)

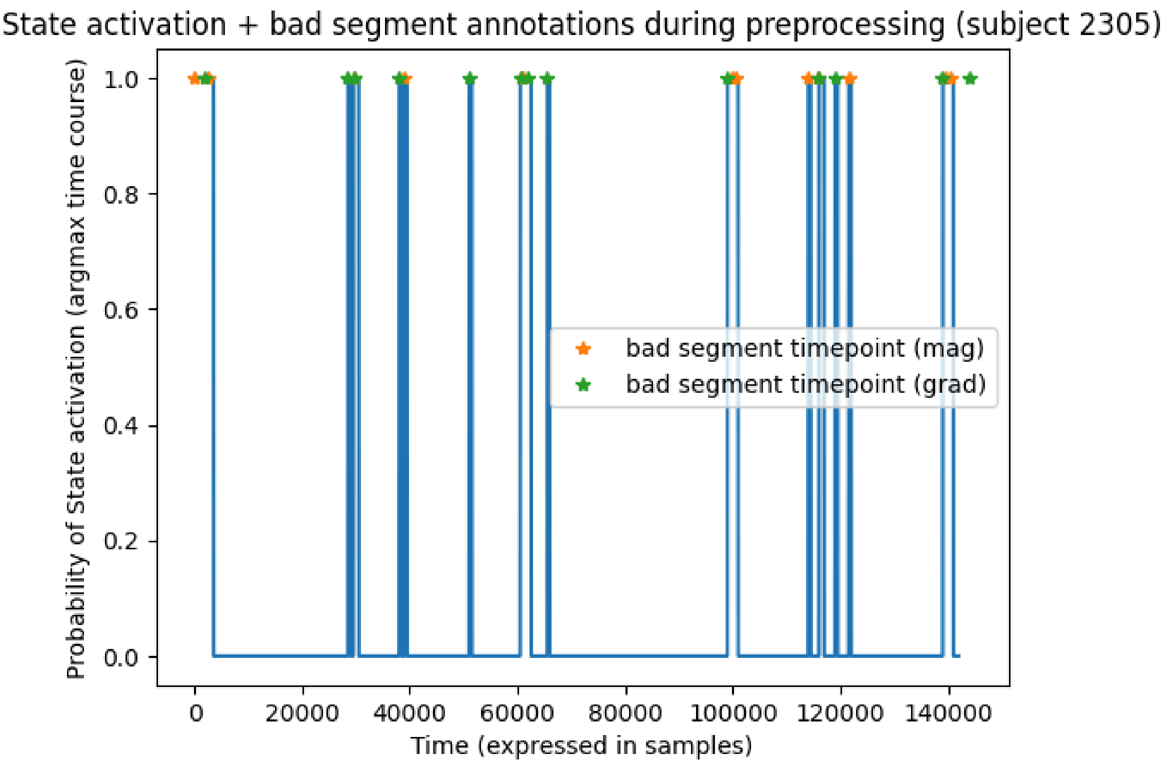
State activation + bad segment annotations during preprocessing (subject 2279)

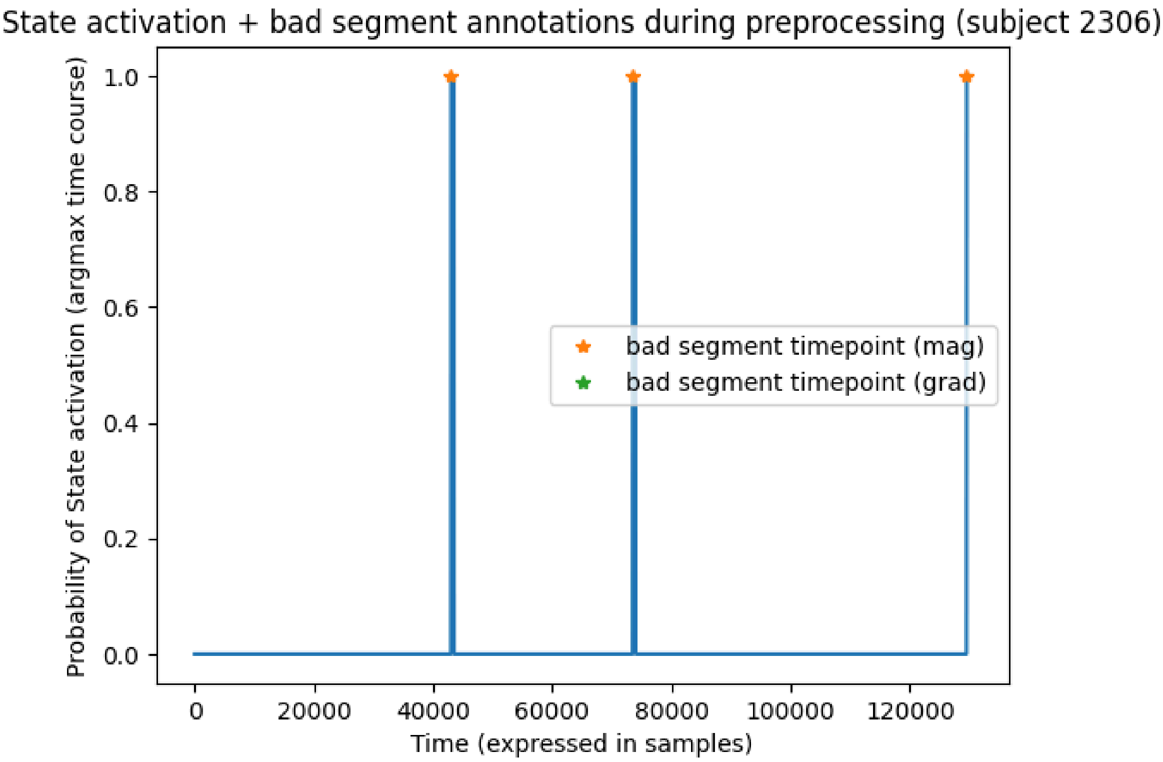


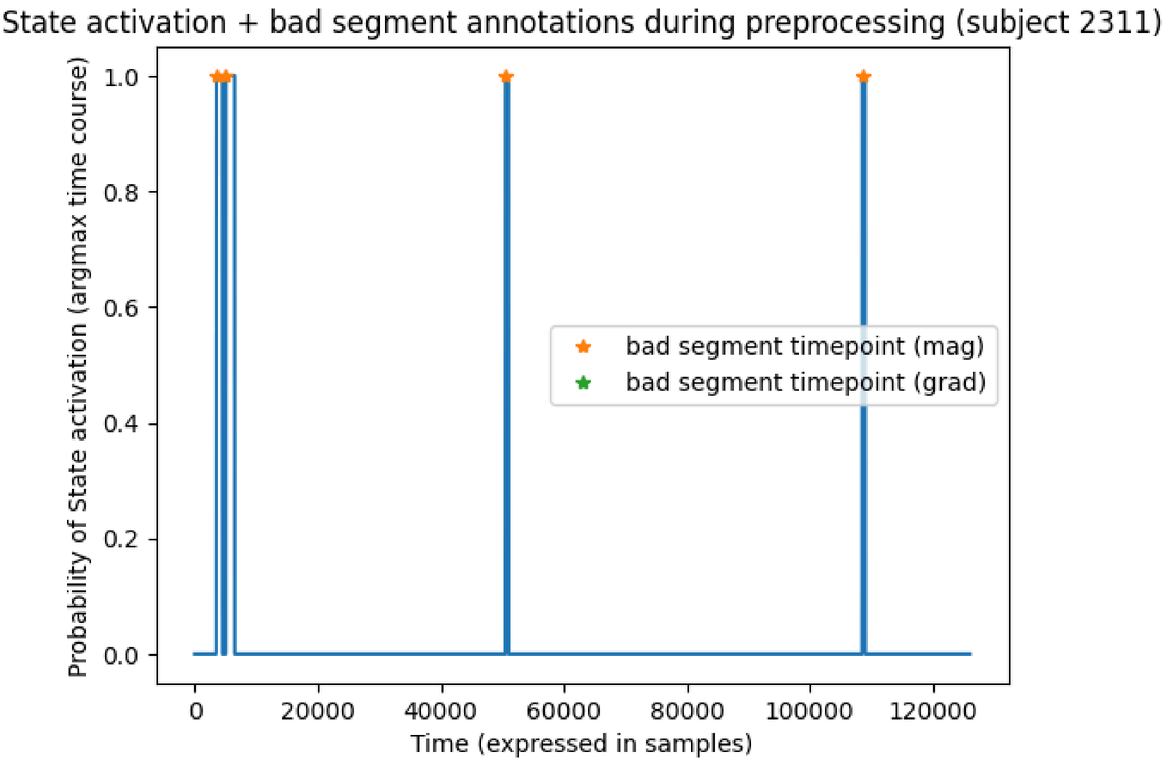
State activation + bad segment annotations during preprocessing (subject 2292)

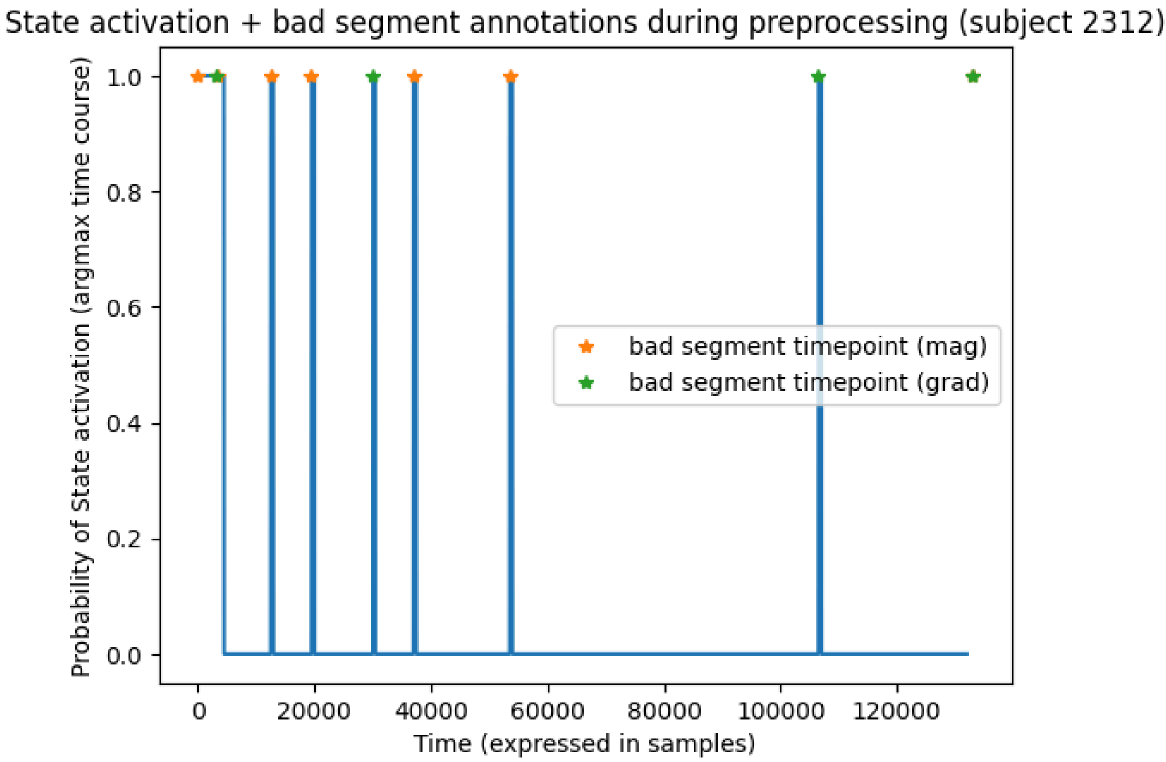


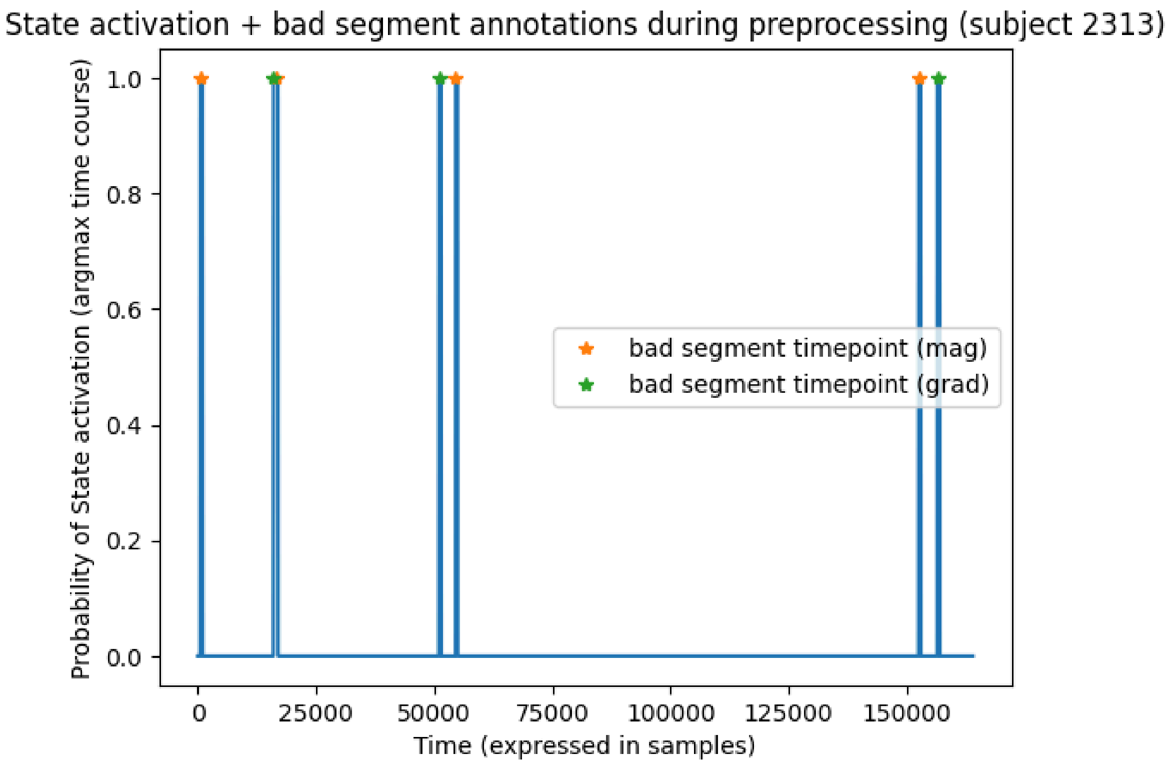

State activation + bad segment annotations during preprocessing (subject 2300)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)

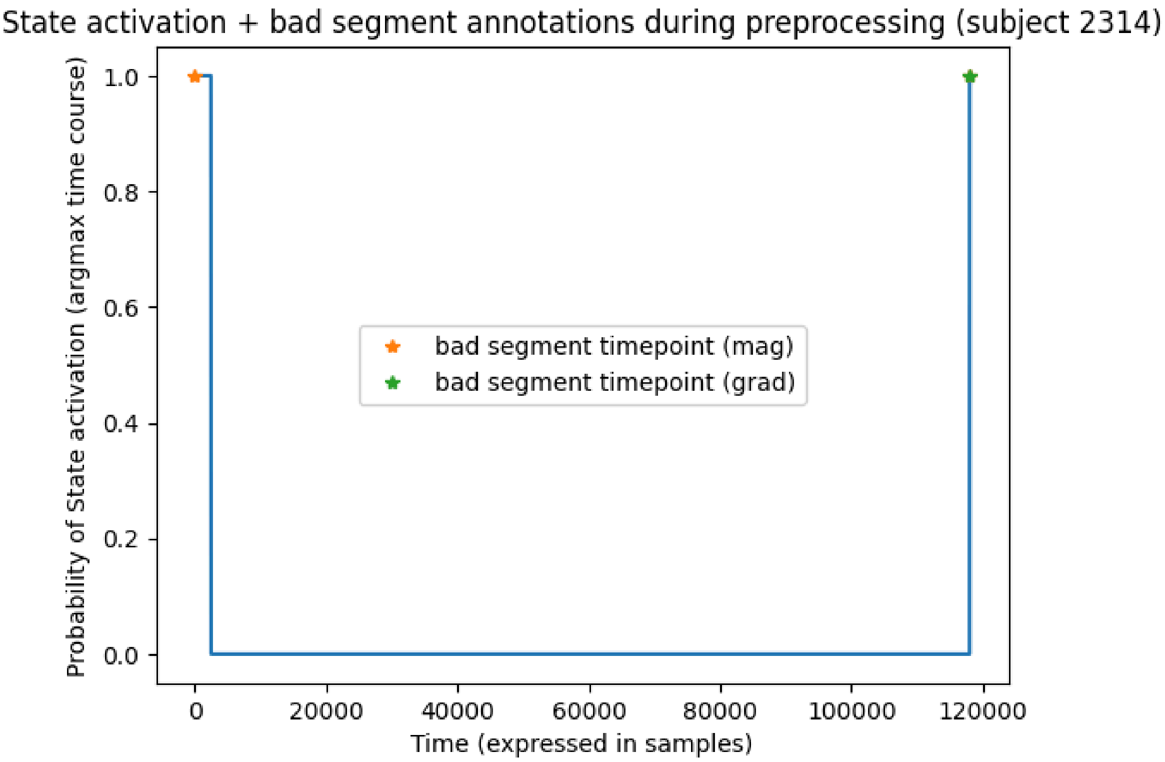

State activation + bad segment annotations during preprocessing (subject 2305)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)

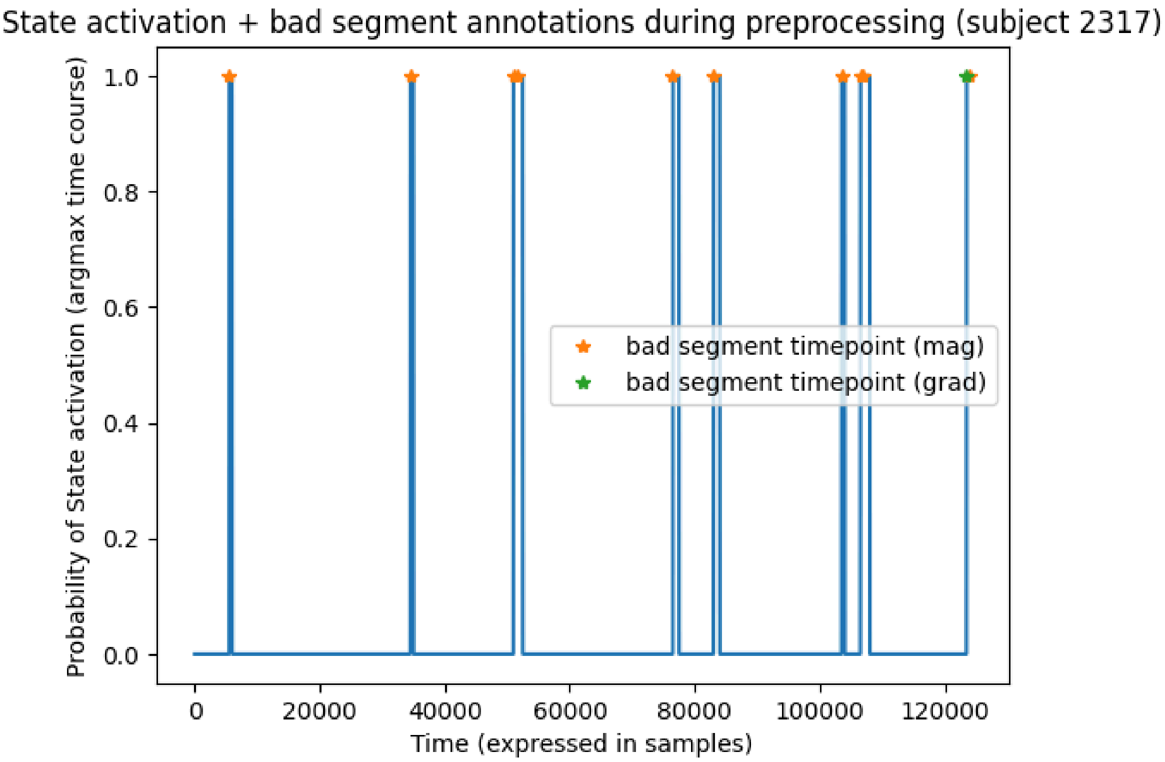

State activation + bad segment annotations during preprocessing (subject 2306)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)

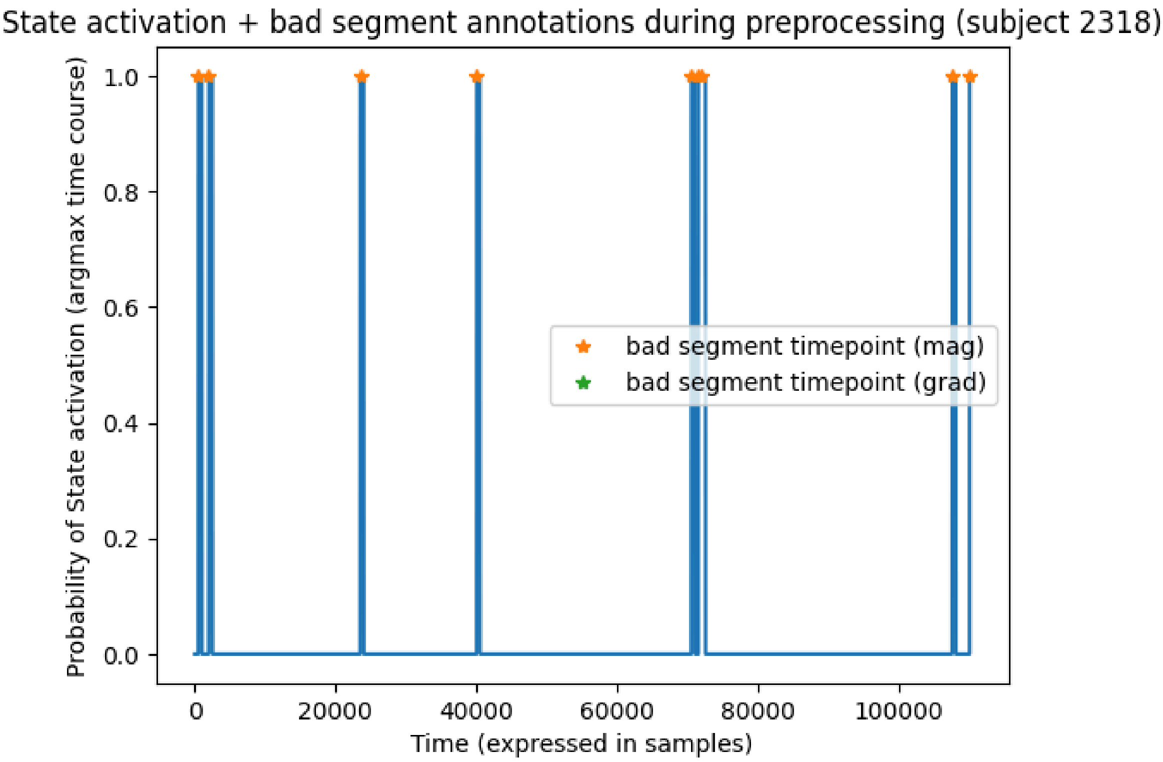

State activation + bad segment annotations during preprocessing (subject 2311)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)

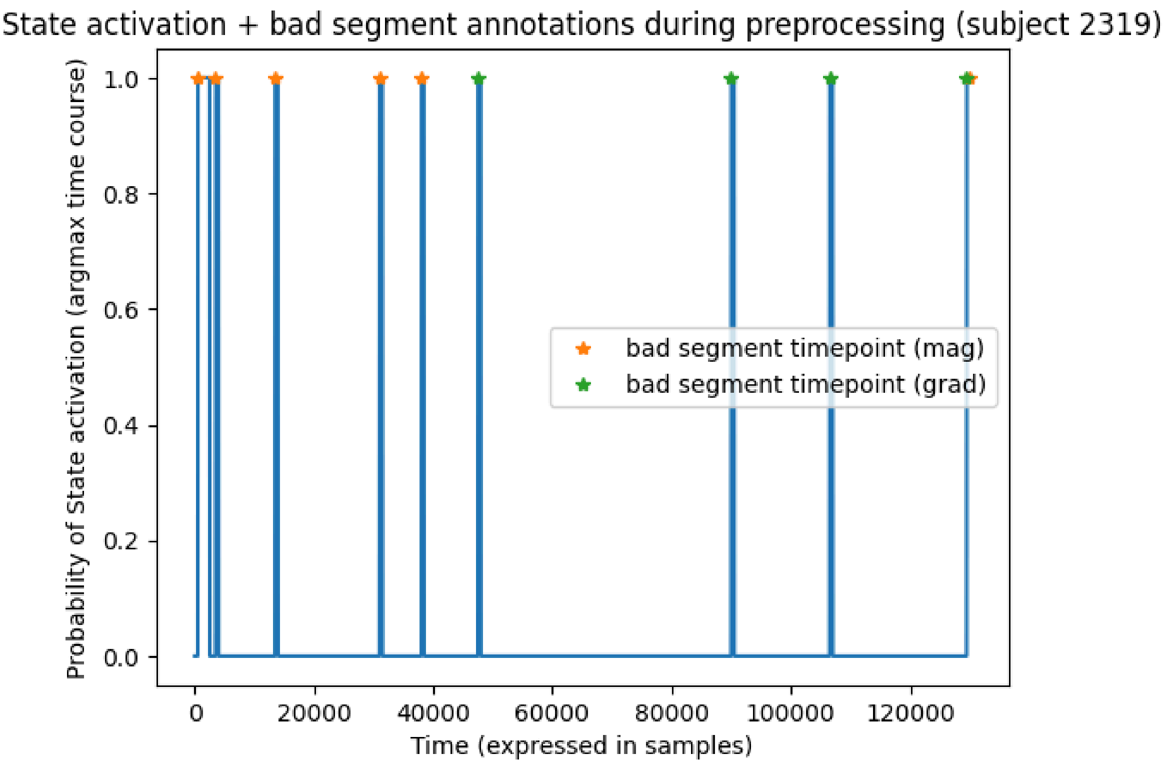

State activation + bad segment annotations during preprocessing (subject 2312)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

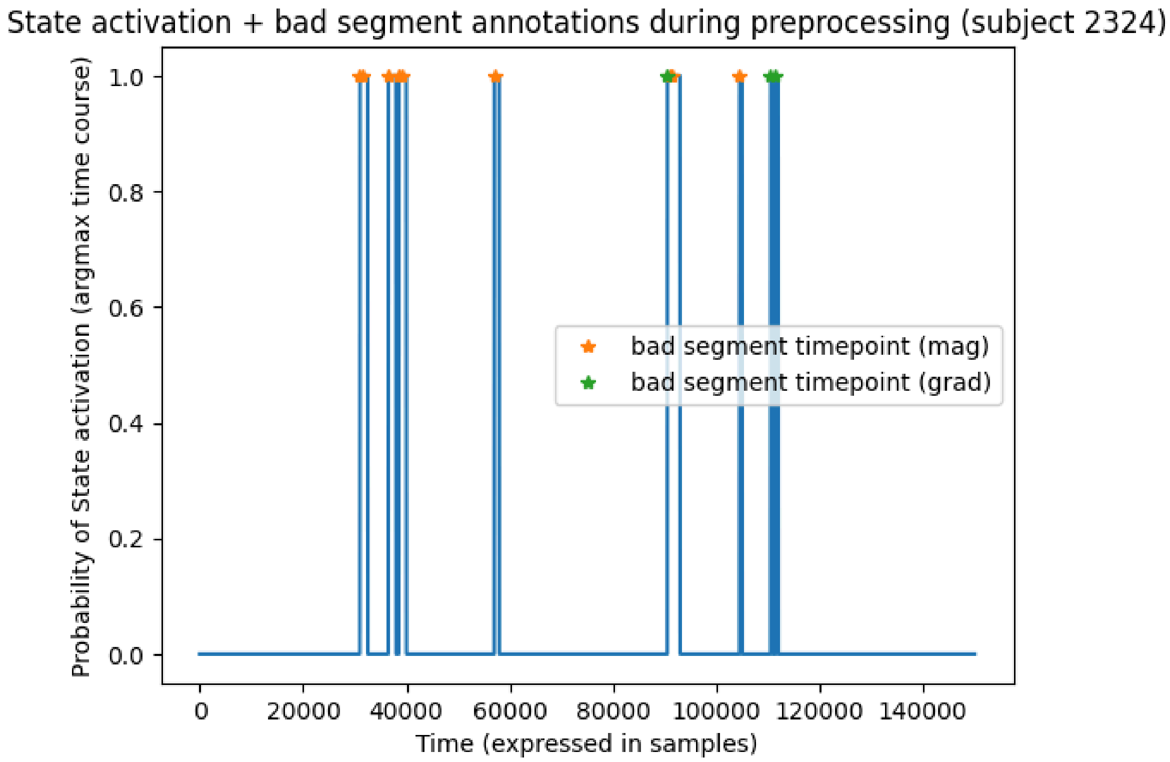

State activation + bad segment annotations during preprocessing (subject 2313)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
25000
50000
75000
100000
125000
150000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

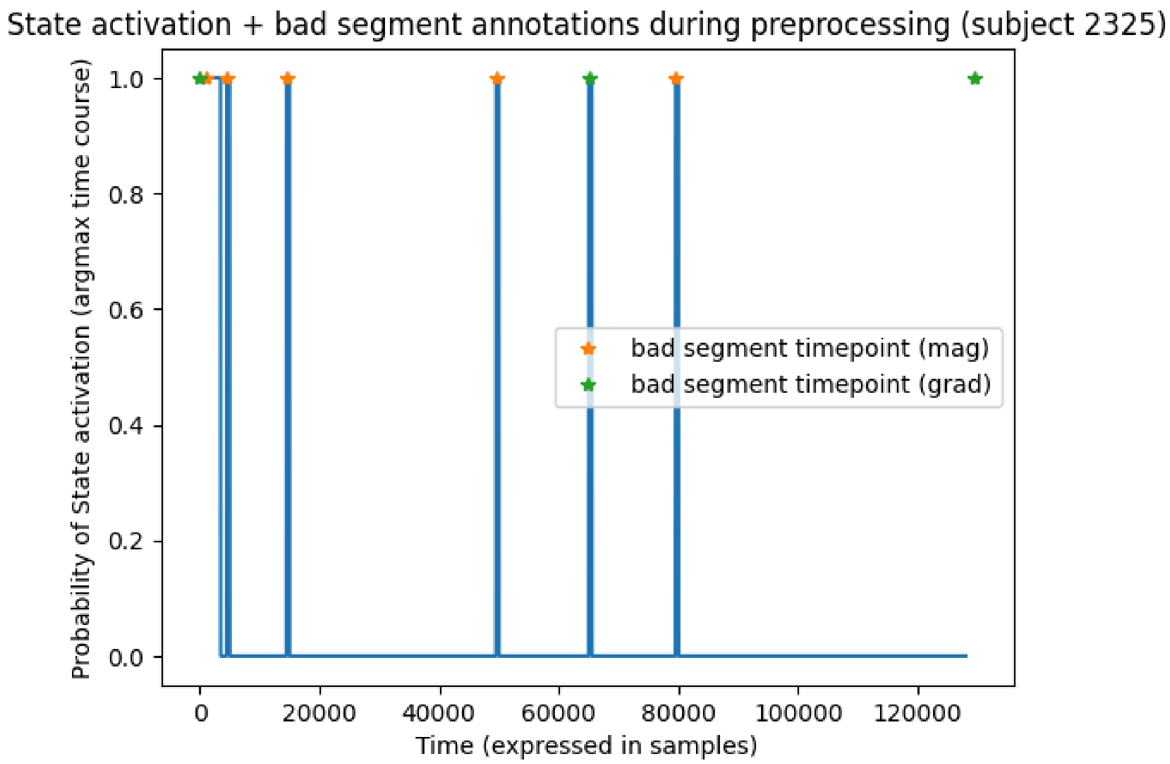

State activation + bad segment annotations during preprocessing (subject 2314)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)


State activation + bad segment annotations during preprocessing (subject 2317)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)

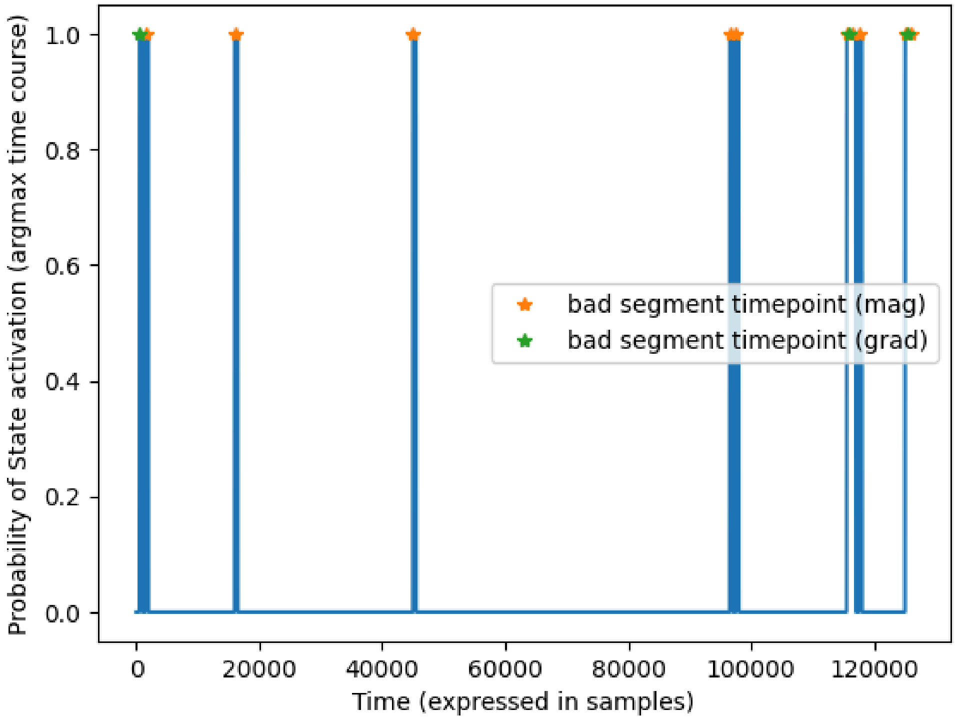

State activation + bad segment annotations during preprocessing (subject 2318)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
Time (expressed in samples)


State activation + bad segment annotations during preprocessing (subject 2319)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)

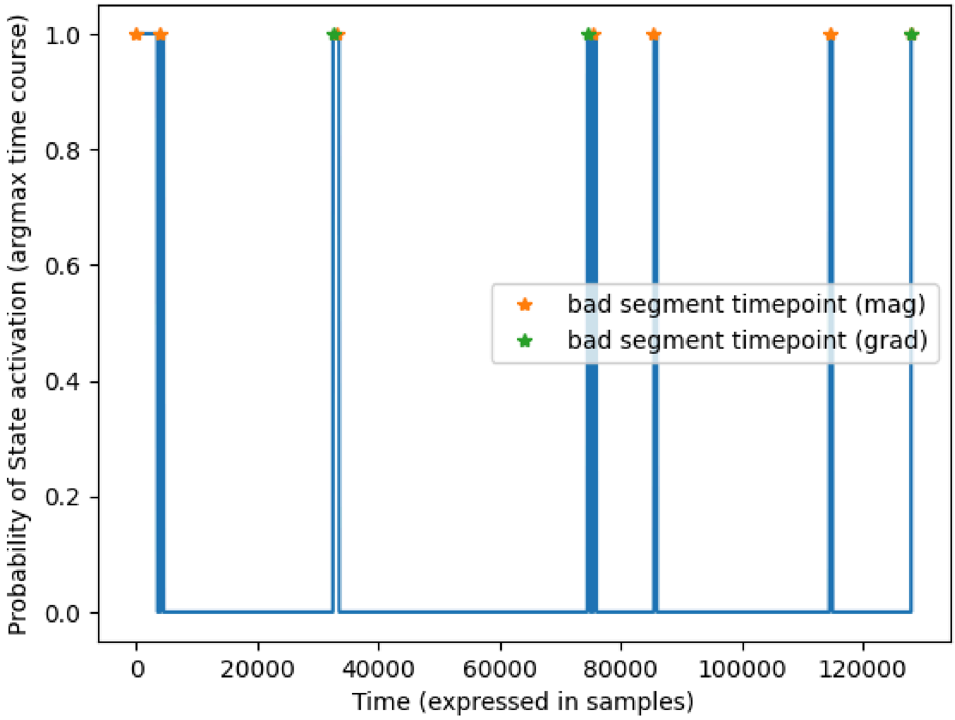

State activation + bad segment annotations during preprocessing (subject 2324)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

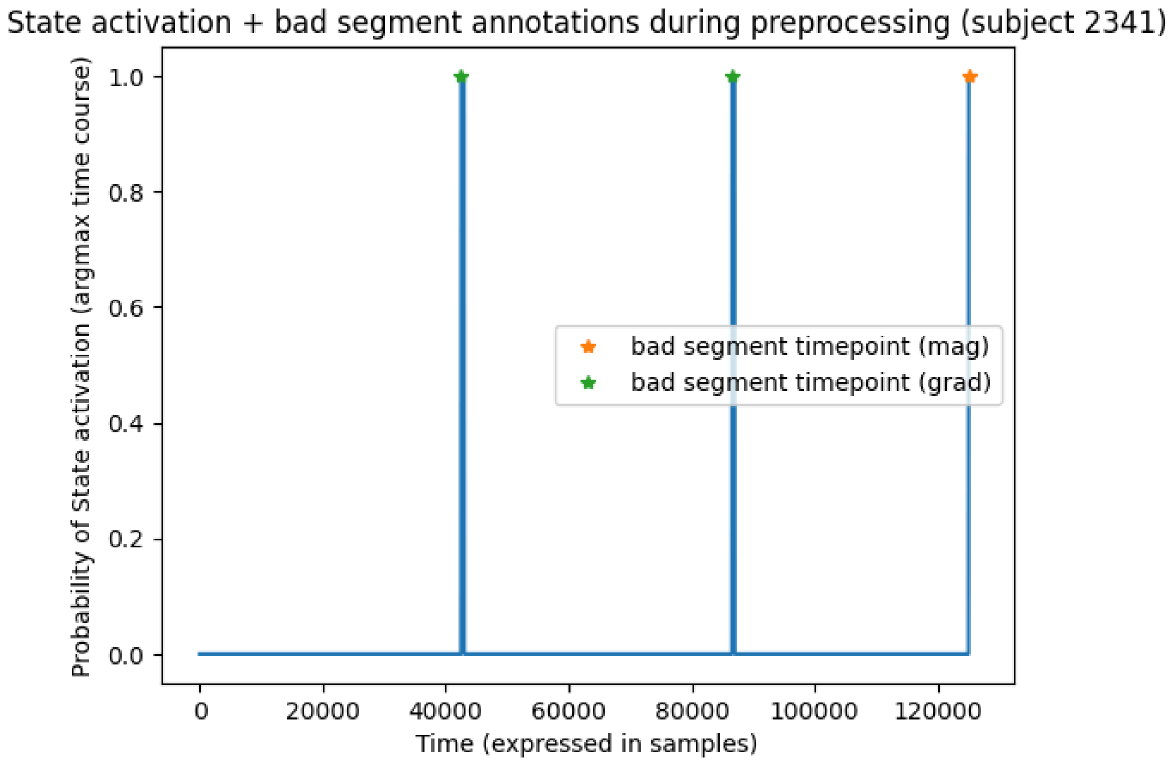

State activation + bad segment annotations during preprocessing (subject 2325)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

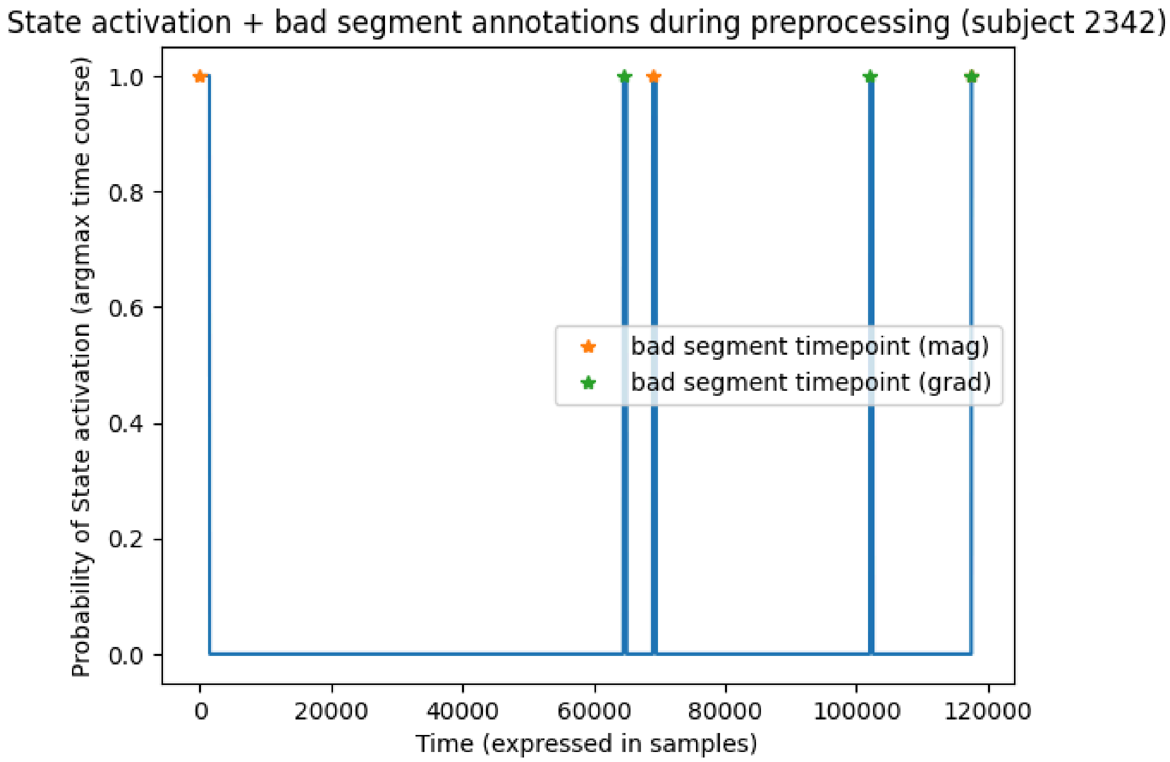
State activation + bad segment annotations during preprocessing (subject 2327)

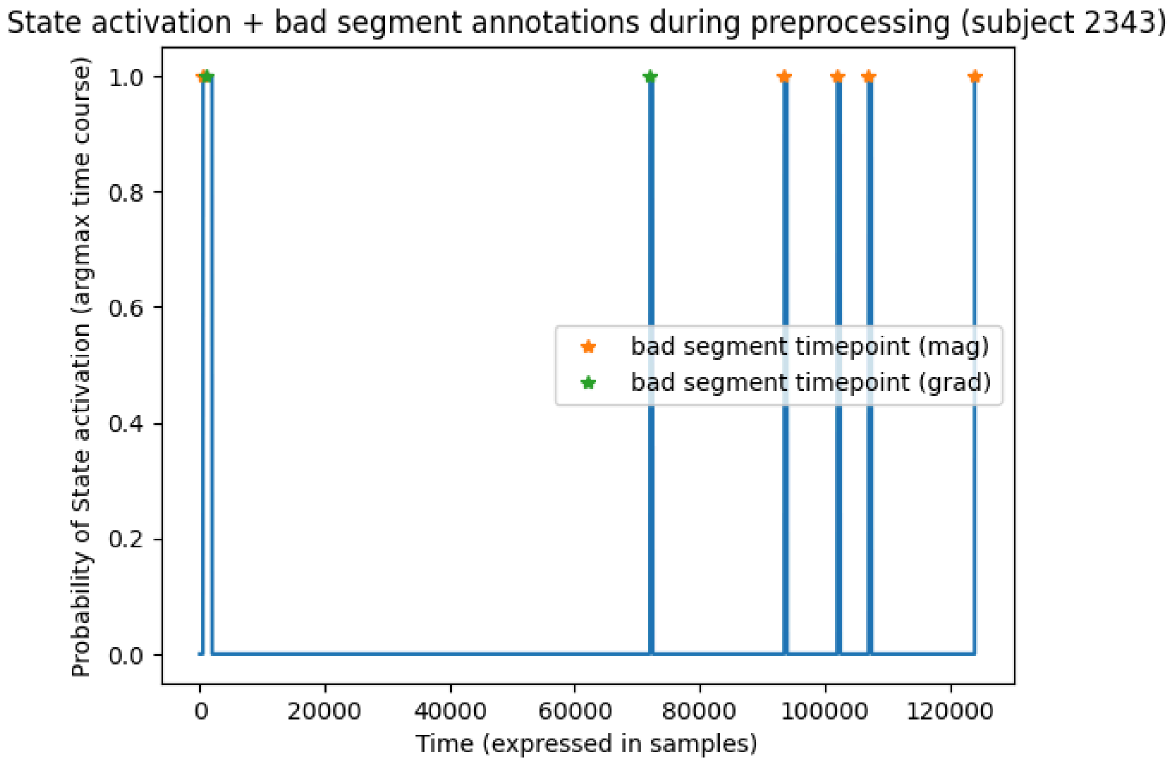


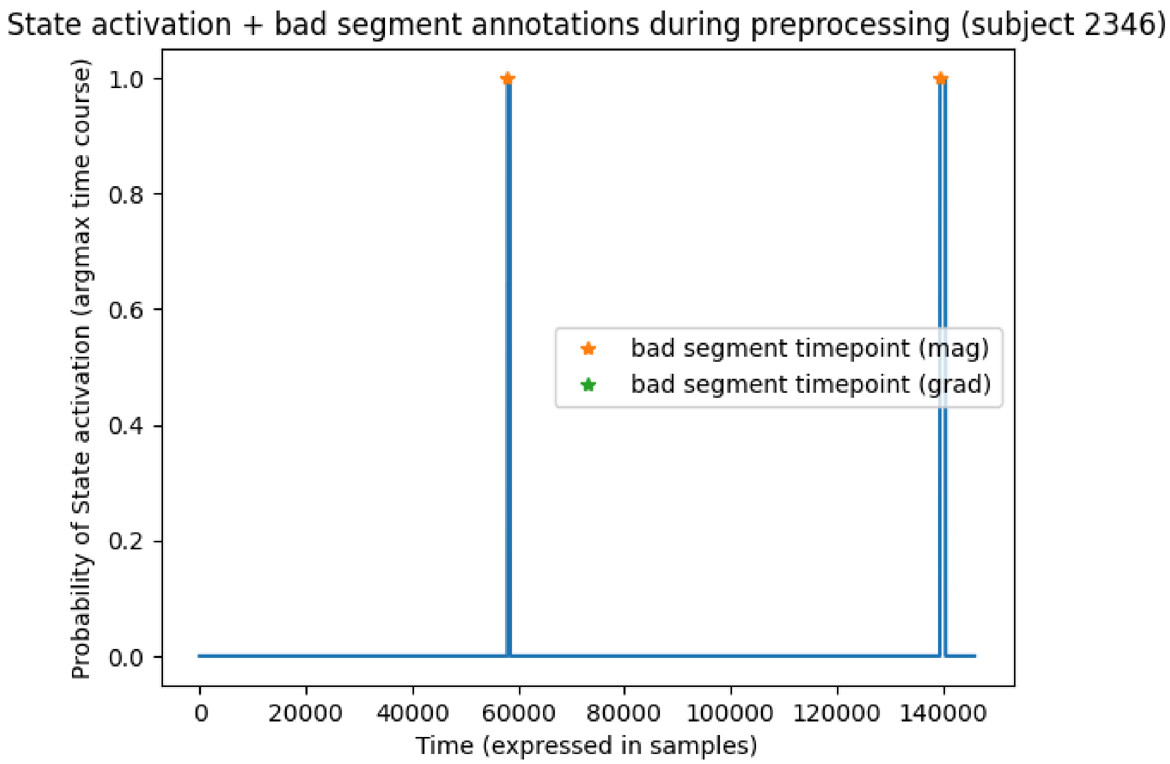
State activation + bad segment annotations during preprocessing (subject 2328)



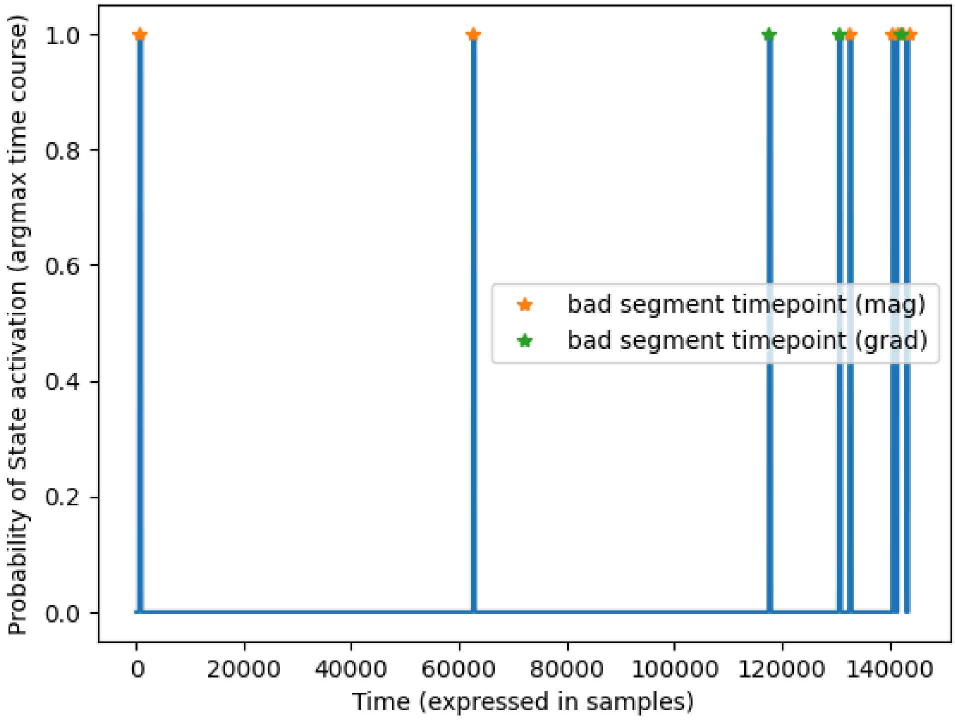

State activation + bad segment annotations during preprocessing (subject 2341)
Probability of State activation (argmax time course)
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)
0.0
0.2
0.4
0.6
0.8
1.0
0
20000
40000
60000
80000
100000
120000


State activation + bad segment annotations during preprocessing (subject 2342)
Probability of State activation (argmax time course)
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)
0.0
0.2
0.4
0.6
0.8
1.0
0
20000
40000
60000
80000
100000
120000

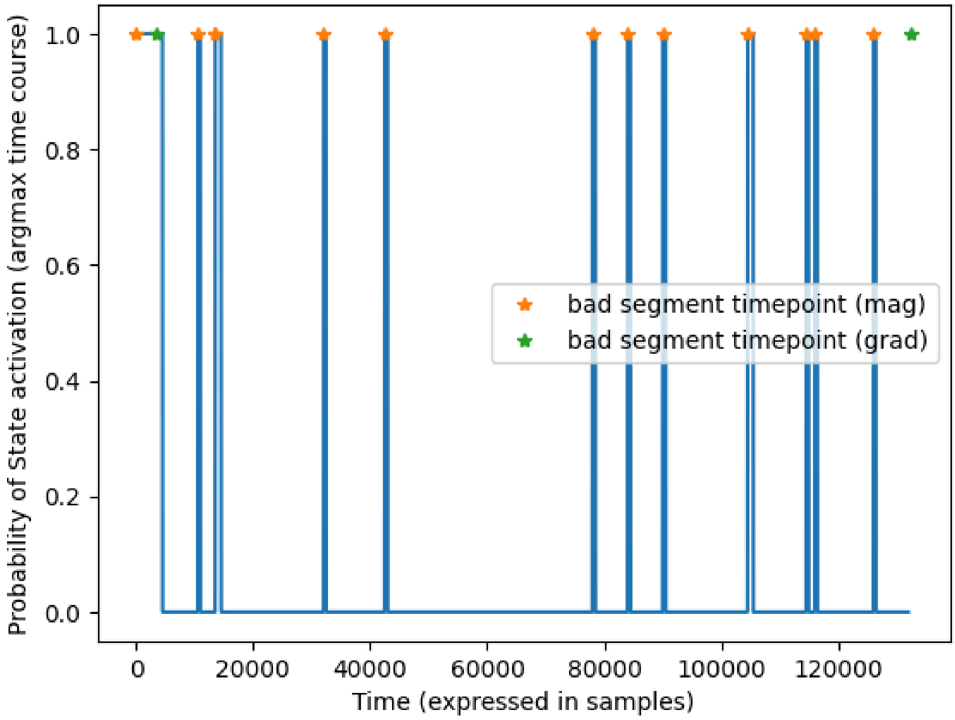

State activation + bad segment annotations during preprocessing (subject 2343)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

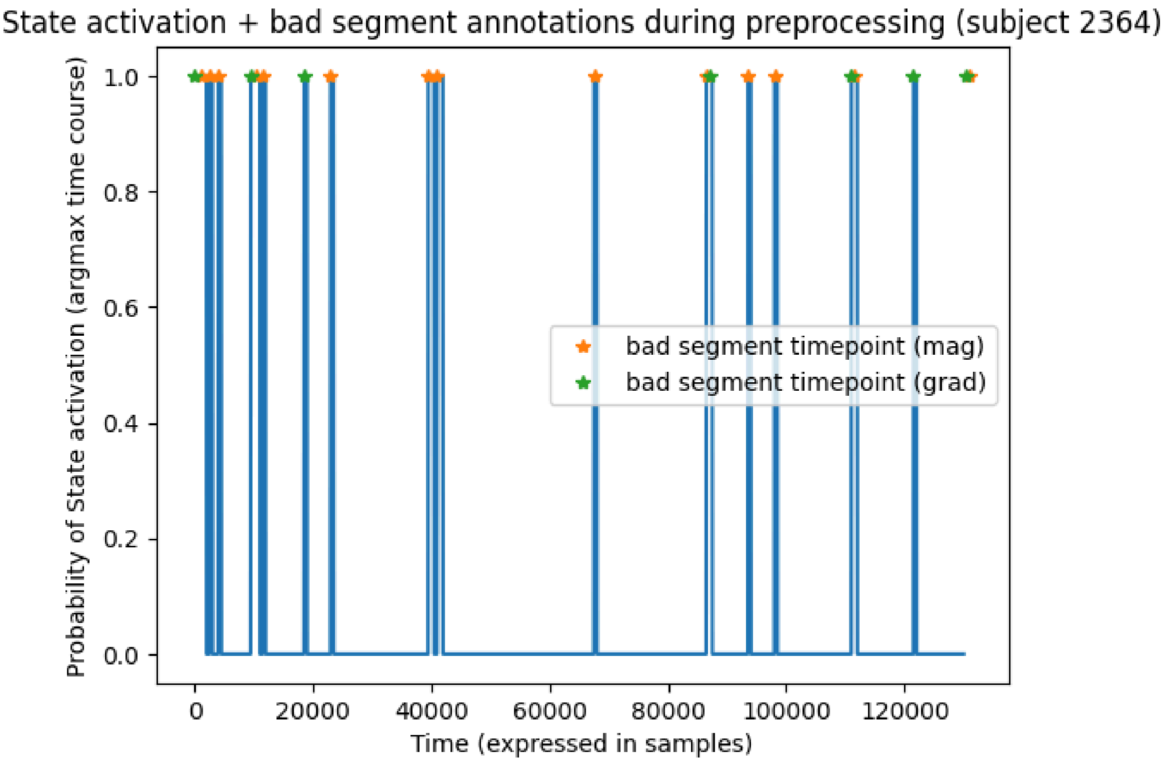

State activation + bad segment annotations during preprocessing (subject 2346)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

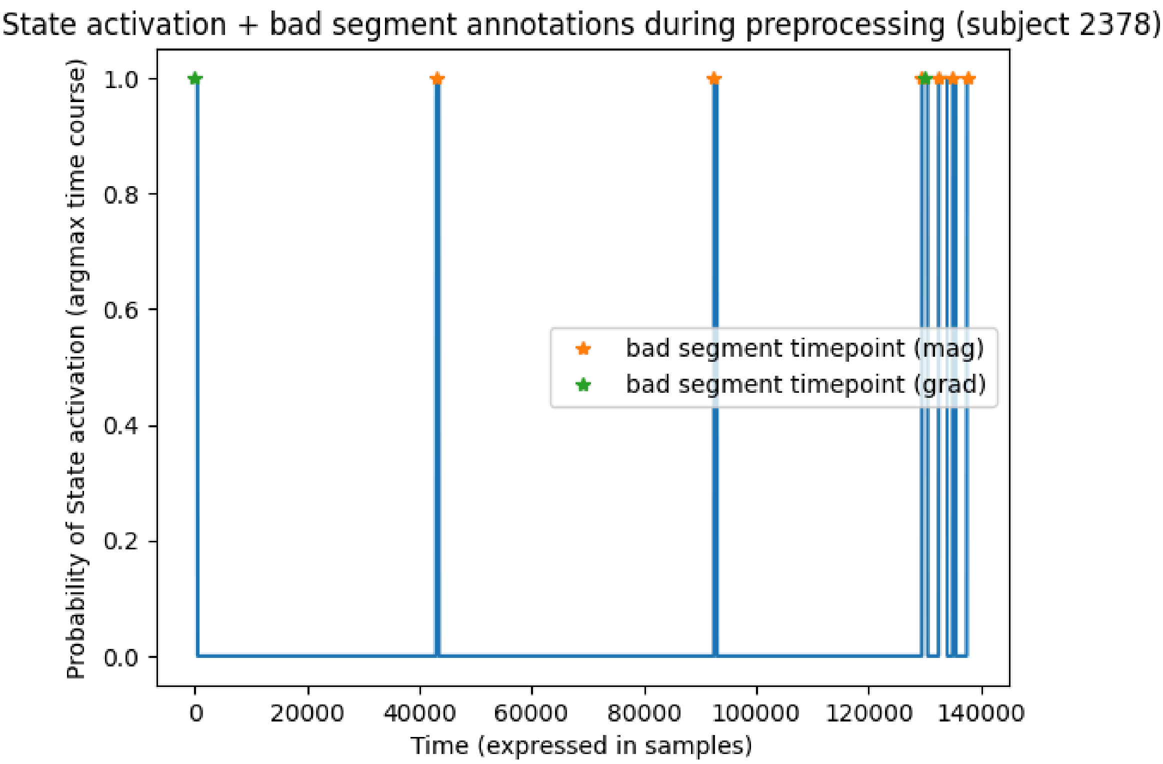
State activation + bad segment annotations during preprocessing (subject 2359)

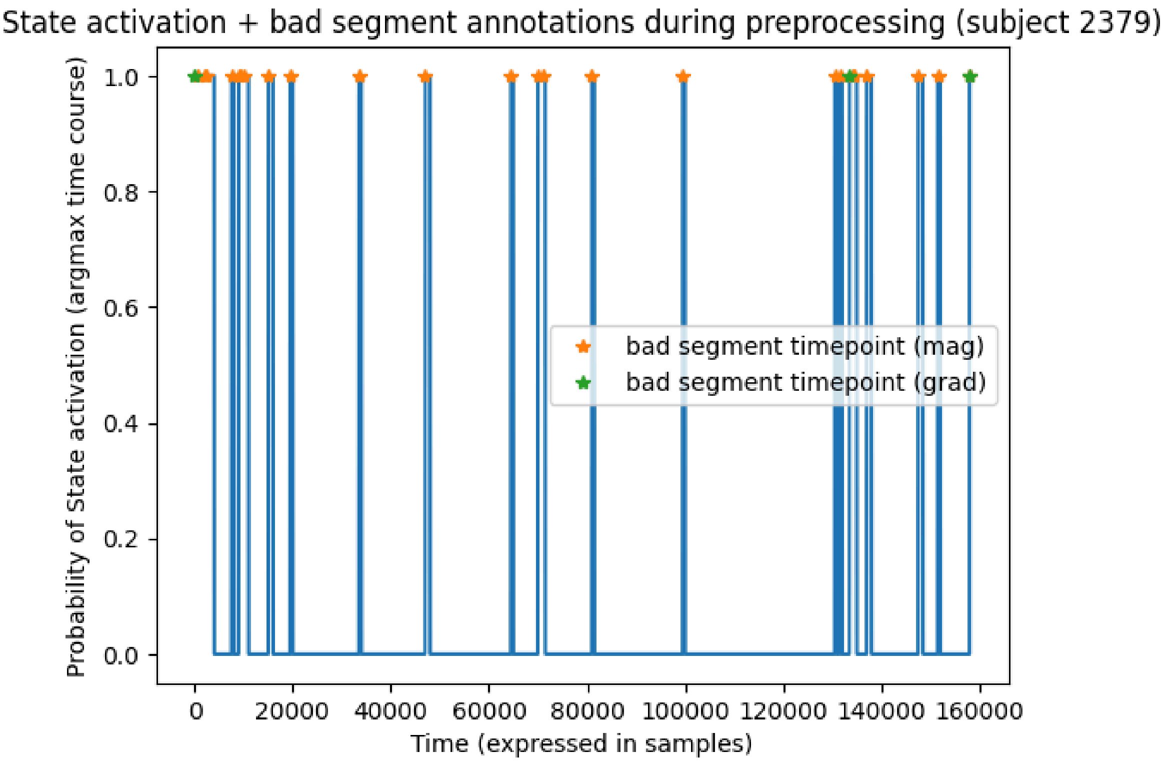


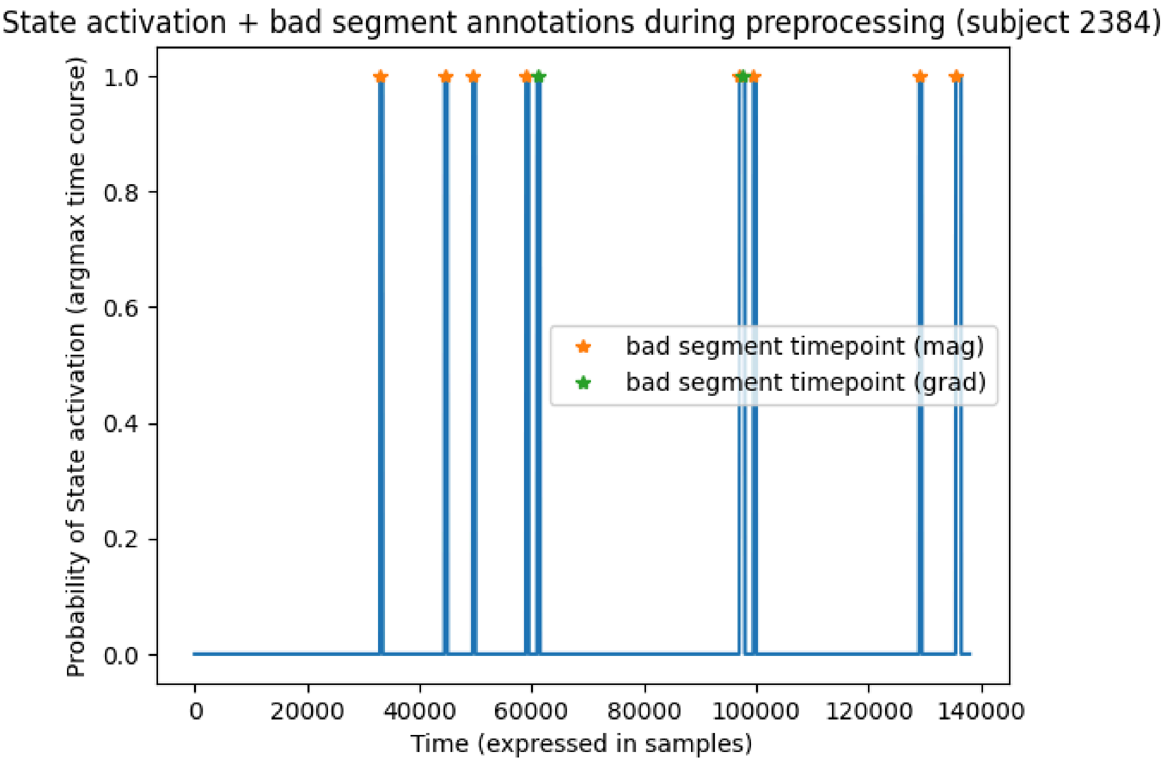
State activation + bad segment annotations during preprocessing (subject 2363)

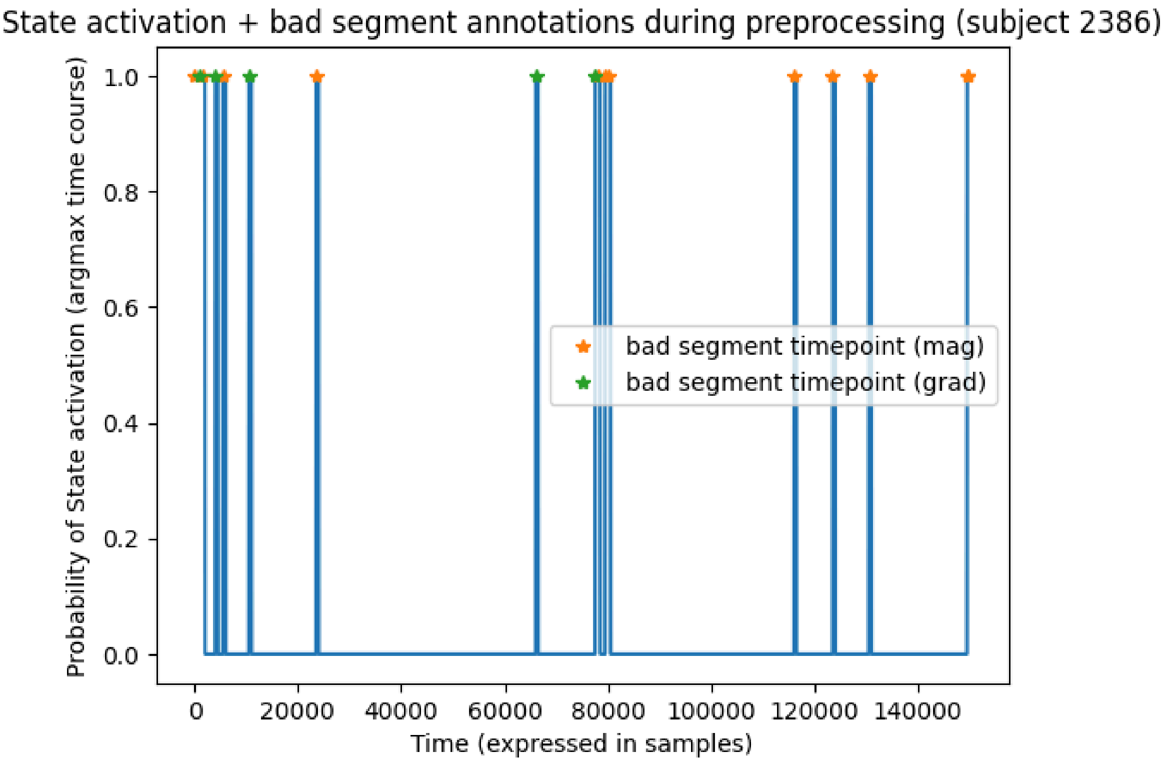


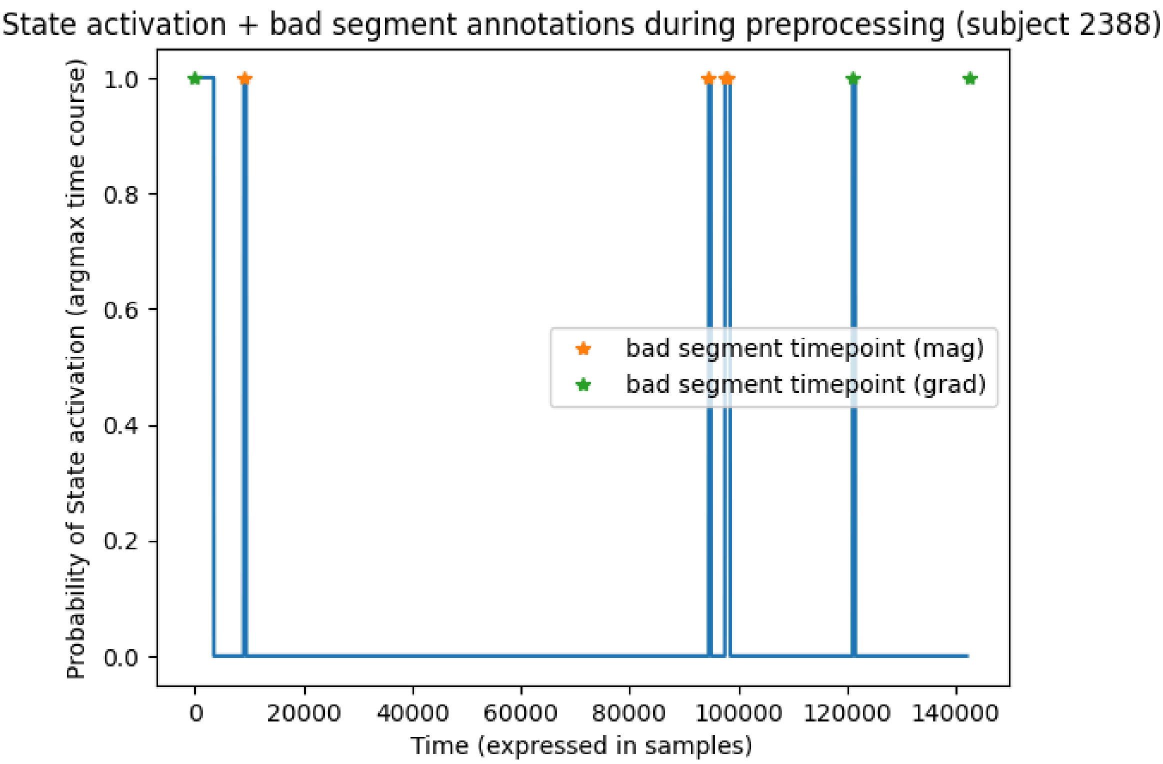

State activation + bad segment annotations during preprocessing (subject 2364)
Probability of State activation (argmax time course)
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000

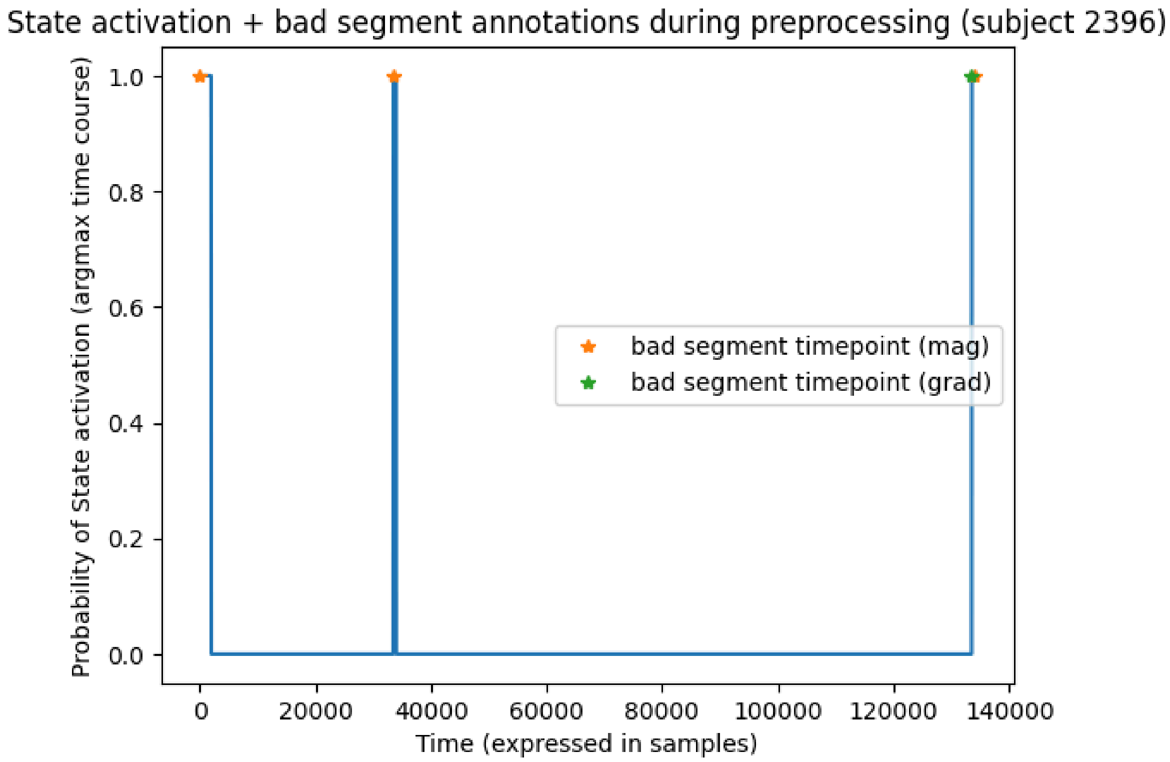

State activation + bad segment annotations during preprocessing (subject 2378)
Probability of State activation (argmax time course)
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000

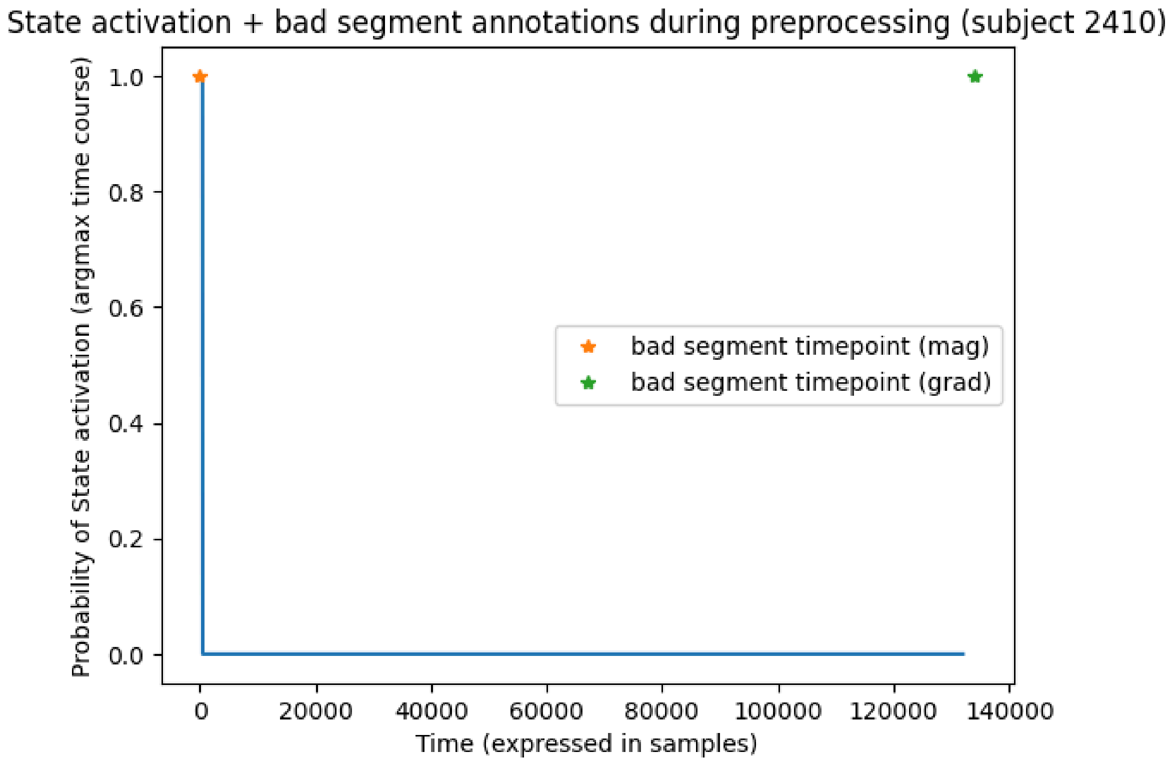

State activation + bad segment annotations during preprocessing (subject 2379)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
160000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

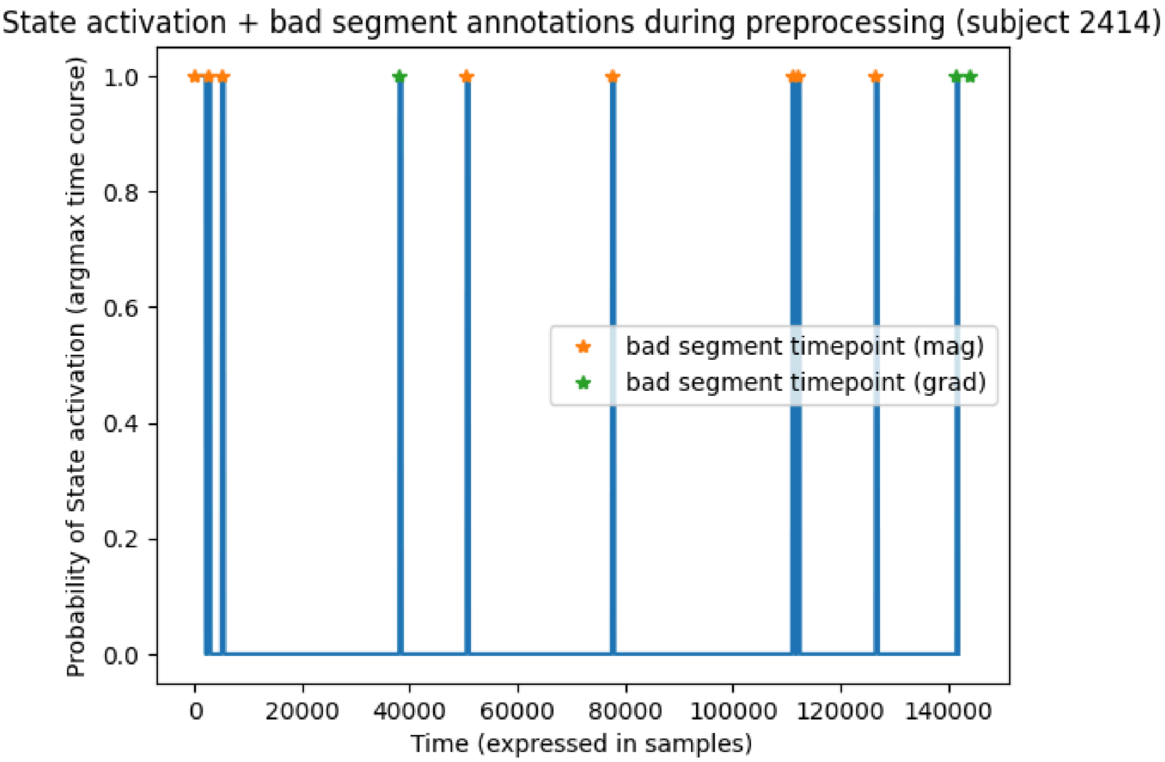

State activation + bad segment annotations during preprocessing (subject 2384)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

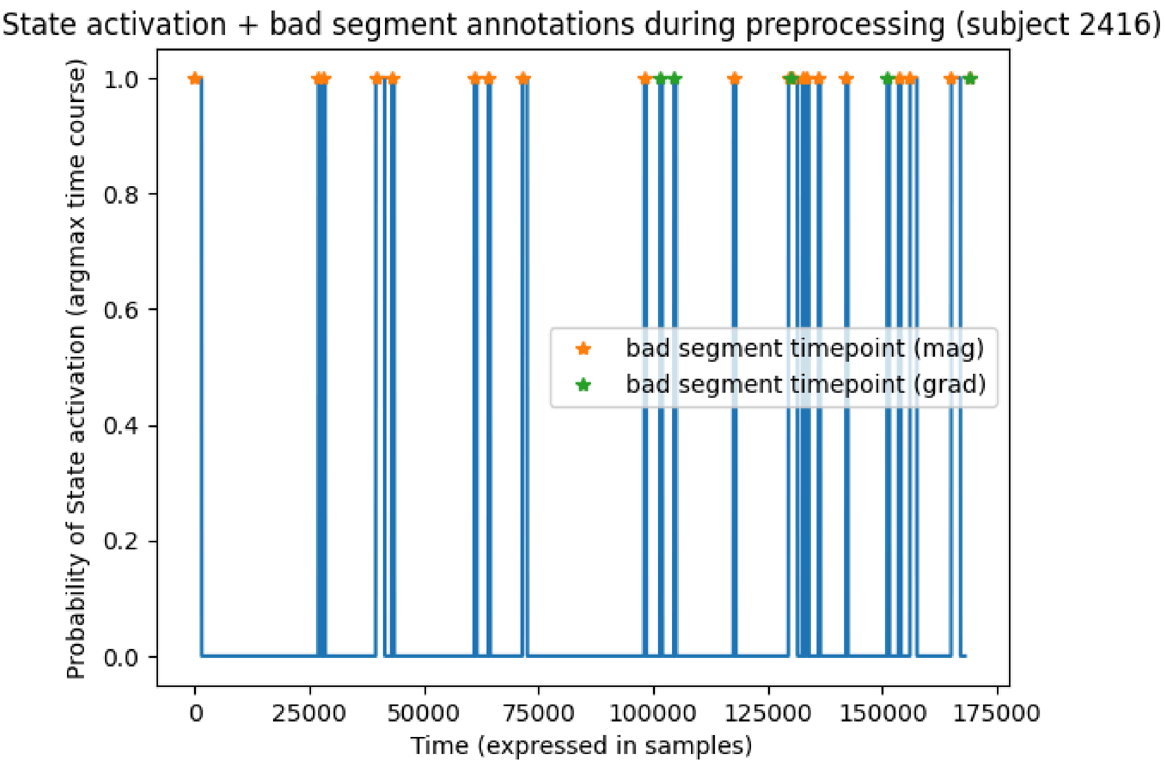

State activation + bad segment annotations during preprocessing (subject 2386)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

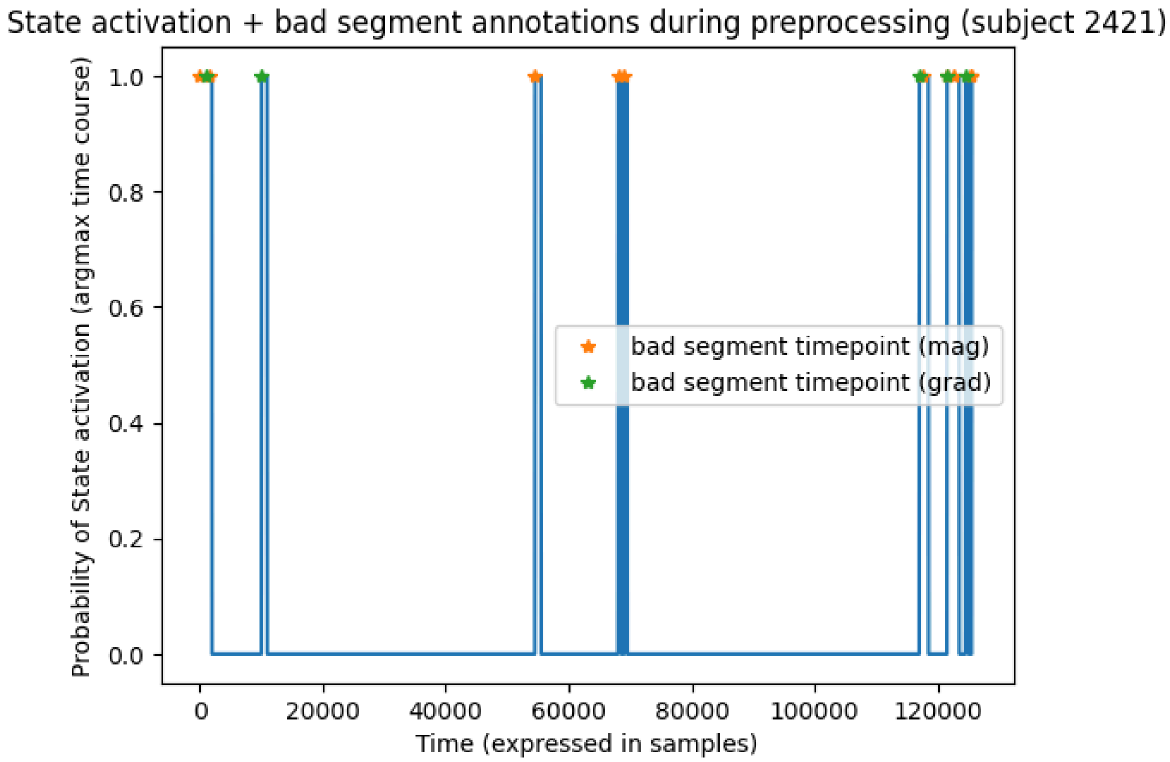

State activation + bad segment annotations during preprocessing (subject 2388)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

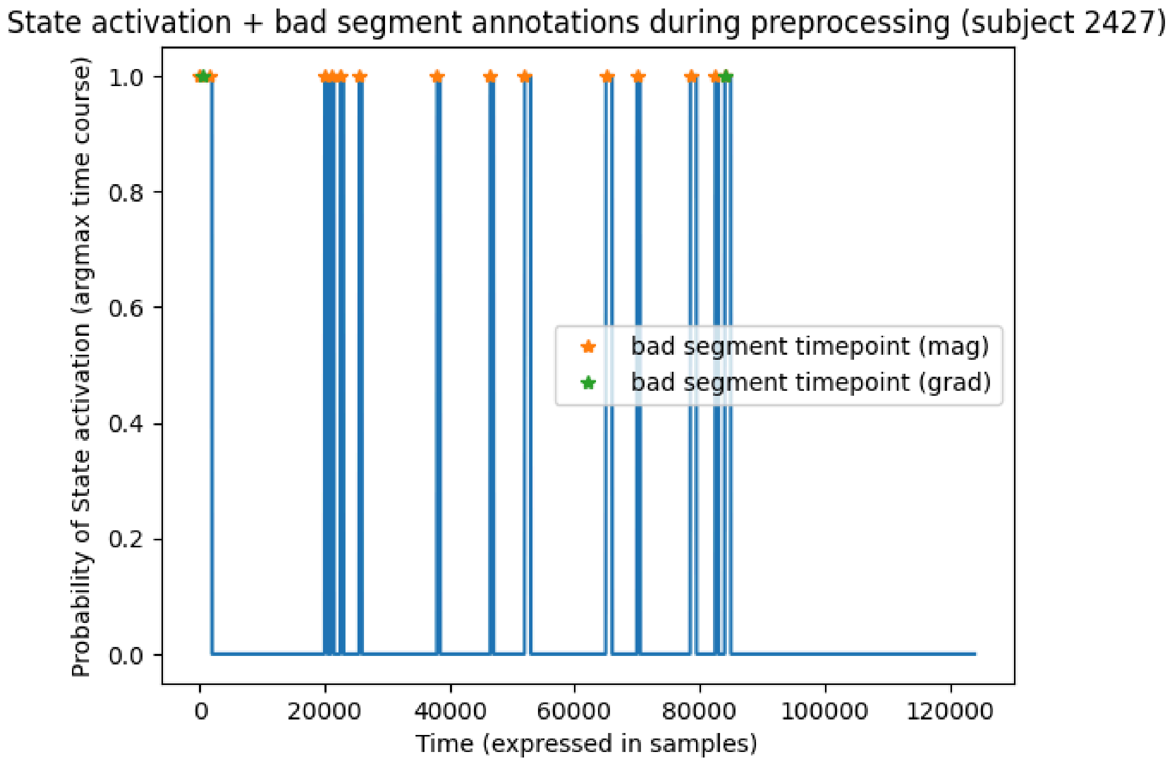

State activation + bad segment annotations during preprocessing (subject 2396)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)

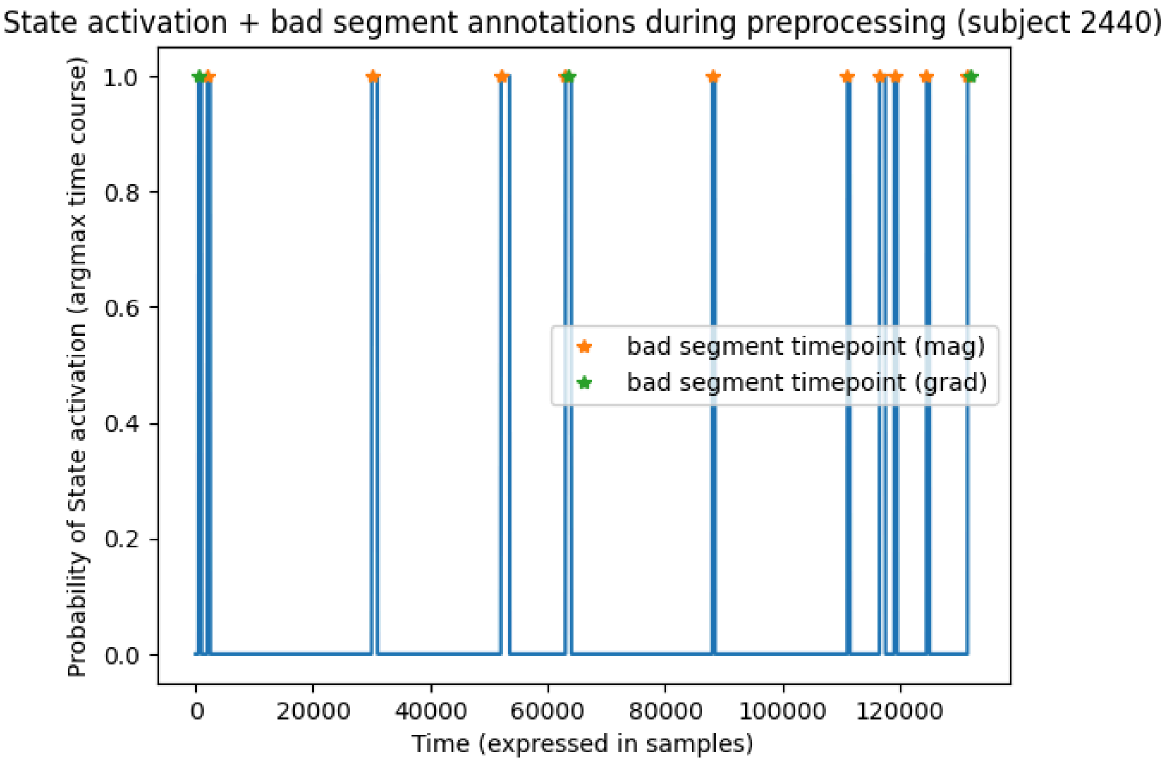

State activation + bad segment annotations during preprocessing (subject 2410)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)

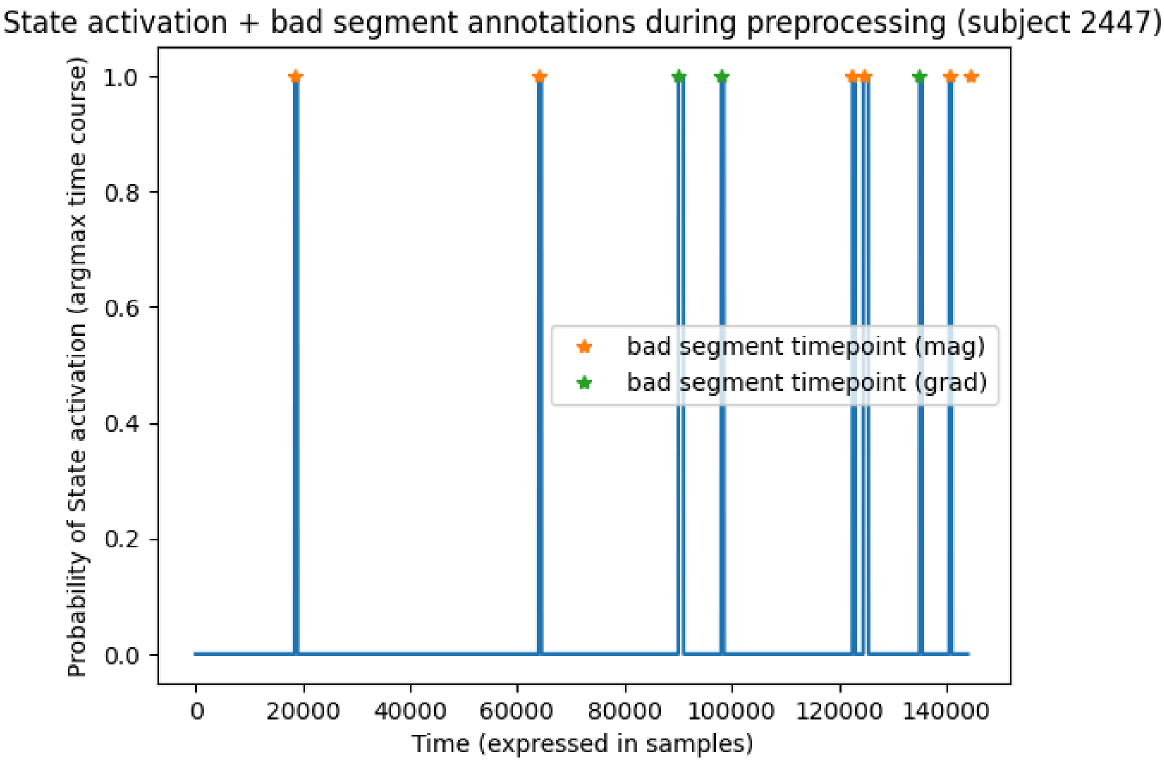

State activation + bad segment annotations during preprocessing (subject 2414)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)

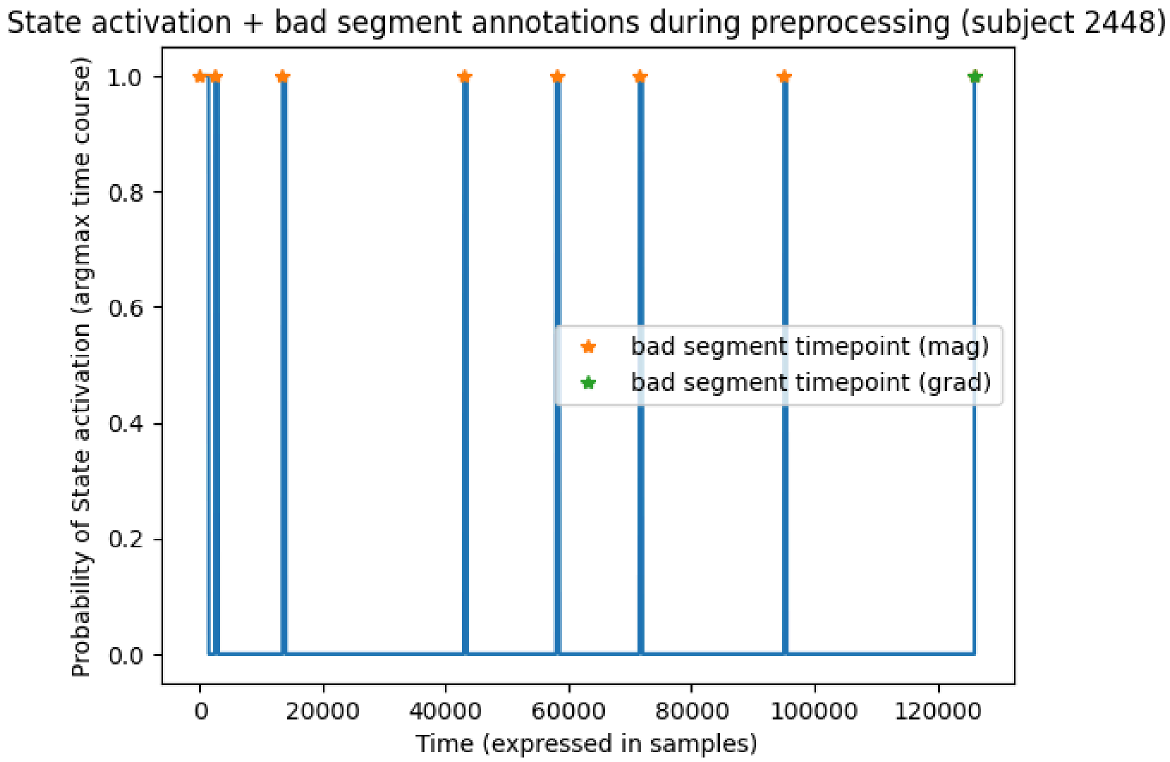

State activation + bad segment annotations during preprocessing (subject 2416)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
0
25000
50000
75000
100000
125000
150000
175000
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)


State activation + bad segment annotations during preprocessing (subject 2421)
Probability of State activation (argmax time course)
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)
0.0
0.2
0.4
0.6
0.8
1.0
0
20000
40000
60000
80000
100000
120000


State activation + bad segment annotations during preprocessing (subject 2427)
Probability of State activation (argmax time course)
Time (expressed in samples)
bad segment timepoint (mag)
bad segment timepoint (grad)
0.0
0.2
0.4
0.6
0.8
1.0
0
20000
40000
60000
80000
100000
120000


State activation + bad segment annotations during preprocessing (subject 2440)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
Time (expressed in samples)


State activation + bad segment annotations during preprocessing (subject 2447)
Probability of State activation (argmax time course)
1.0
0.8
0.6
0.4
0.2
0.0
bad segment timepoint (mag)
bad segment timepoint (grad)
0
20000
40000
60000
80000
100000
120000
140000
Time (expressed in samples)



Let's also plot a time-window before & after the start of a few "bad segment" instances

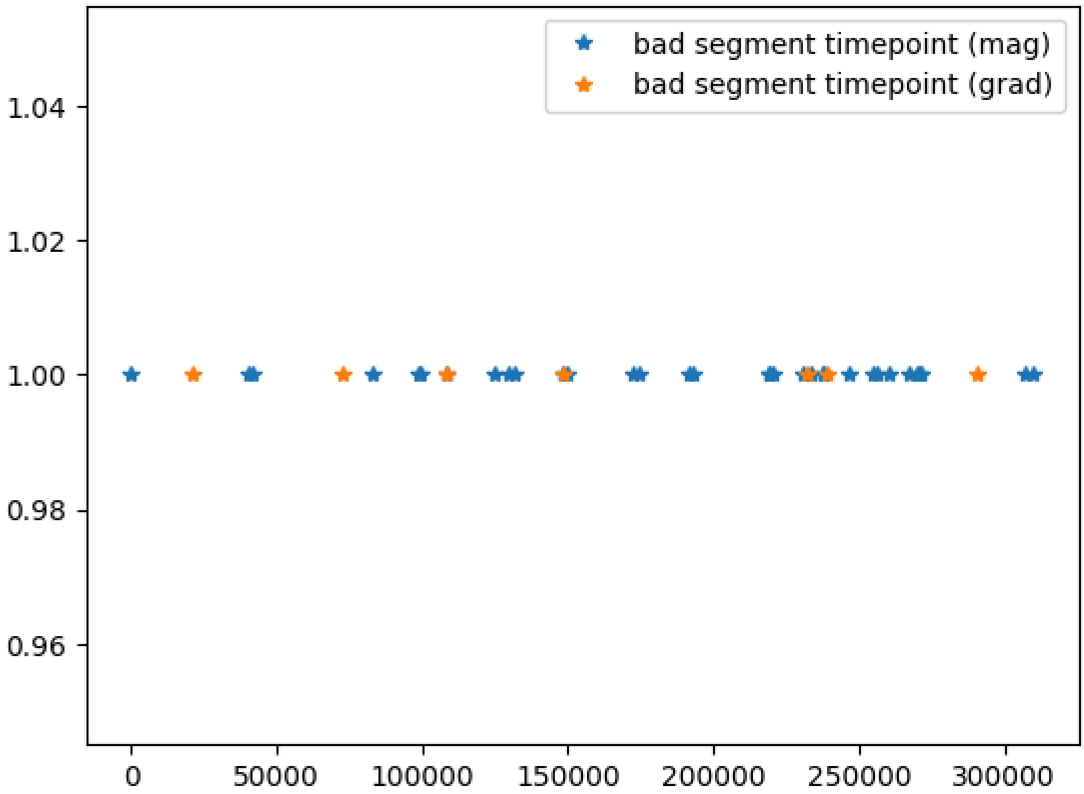
In [99]:

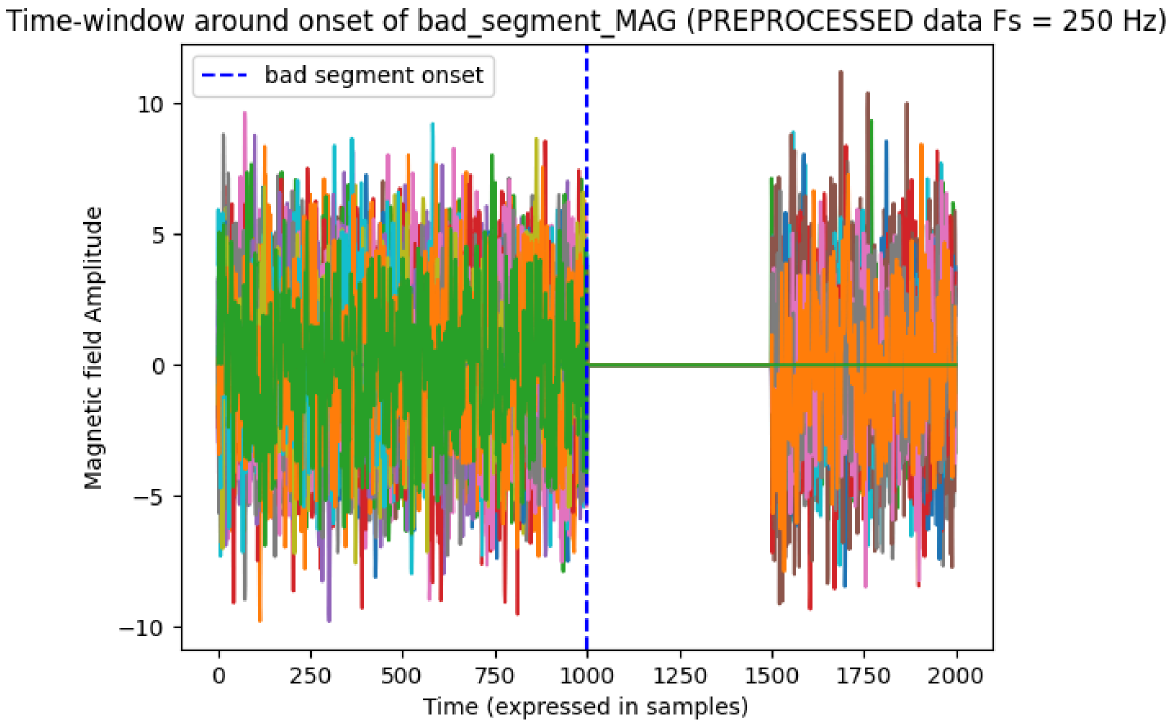
```
# ex. subject 3

loaded = mne.io.read_raw_fif(input_data_HMM[2], verbose=False)

# Get annotations
annotations = loaded.annotations

# Find timepoints with 'bad_segment_mag' or 'bad_segment_grad' annotations
bad_segment_mag_idx = [i for i, description in enumerate(annotations.descrip
bad_segment_grad_idx = [i for i, description in enumerate(annotations.descri

# Get timepoints corresponding to the indices
bad_segment_mag_timepoints = annotations.onset[bad_segment_mag_idx]
bad_segment_grad_timepoints = annotations.onset[bad_segment_grad_idx]

bad_segment_mag_timepoints = [(timepoint - loaded.first_samp/250.0)*250 for
bad_segment_grad_timepoints = [(timepoint - loaded.first_samp/250.0)*250 for

#print("Timepoints with 'bad_segment_mag' annotation:", bad_segment_mag_time
#print("Timepoints with 'bad_segment_grad' annotation:", bad_segment_grad_ti

print(len(bad_segment_mag_timepoints))
print(len(bad_segment_grad_timepoints))

plt.plot(bad_segment_mag_timepoints, np.ones_like(bad_segment_mag_timepoints
plt.plot(bad_segment_grad_timepoints, np.ones_like(bad_segment_grad_timepoir
plt.legend()

toplot_MEG = loaded.get_data()
plt.figure()
for segment in range(len(bad_segment_mag_timepoints)):
    plt.plot(toplot_MEG[5][int(bad_segment_mag_timepoints[segment] - 1000):i
plt.axvline(x = 1000, color = 'b', linestyle='dashed', label='bad segment or
plt.xlabel('Time (expressed in samples)')
```

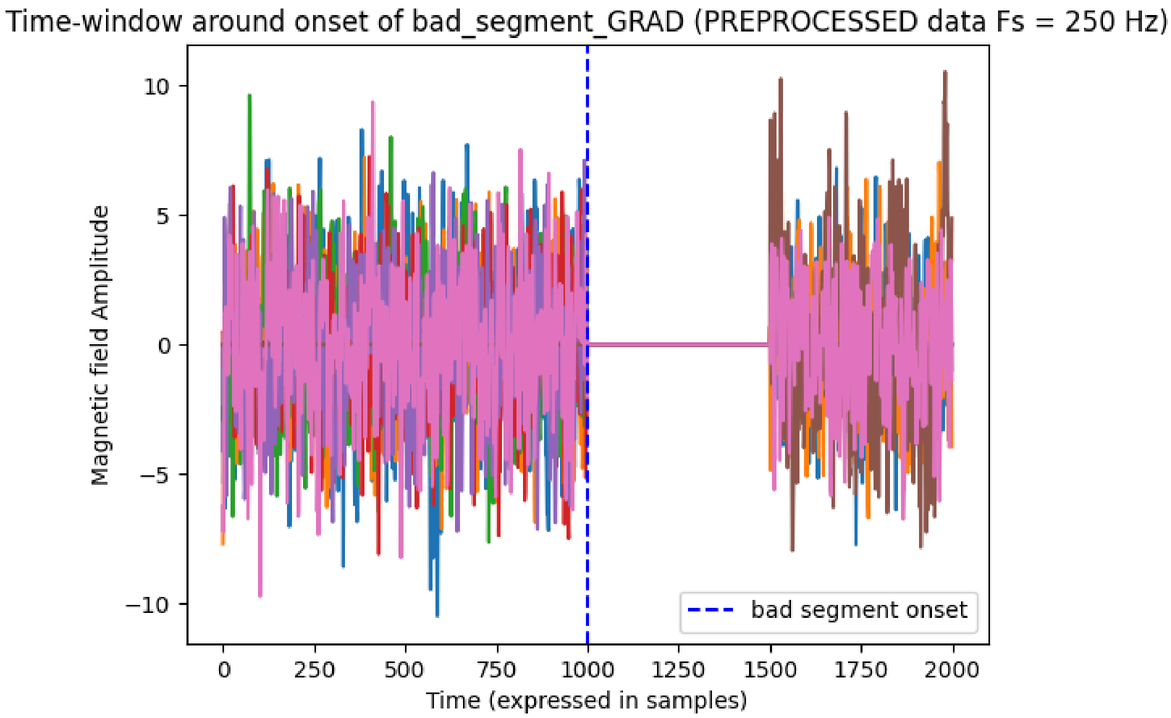
```
plt.ylabel('Magnetic field Amplitude')
plt.title('Time-window around onset of bad_segment_MAG (PREPROCESSED data Fs
plt.legend()

plt.figure()
for segment in range(len(bad_segment_grad_timepoints)):
    plt.plot(toplot_MEG[5][int(bad_segment_grad_timepoints[segment] - 1000):
plt.axvline(x = 1000, color = 'b', linestyle='dashed', label='bad segment or
plt.xlabel('Time (expressed in samples)')
plt.ylabel('Magnetic field Amplitude')
plt.title('Time-window around onset of bad_segment_GRAD (PREPROCESSED data F
plt.legend()
```

```
33
7
```

Out[99]: `<matplotlib.legend.Legend at 0x7efbe10f7070>`



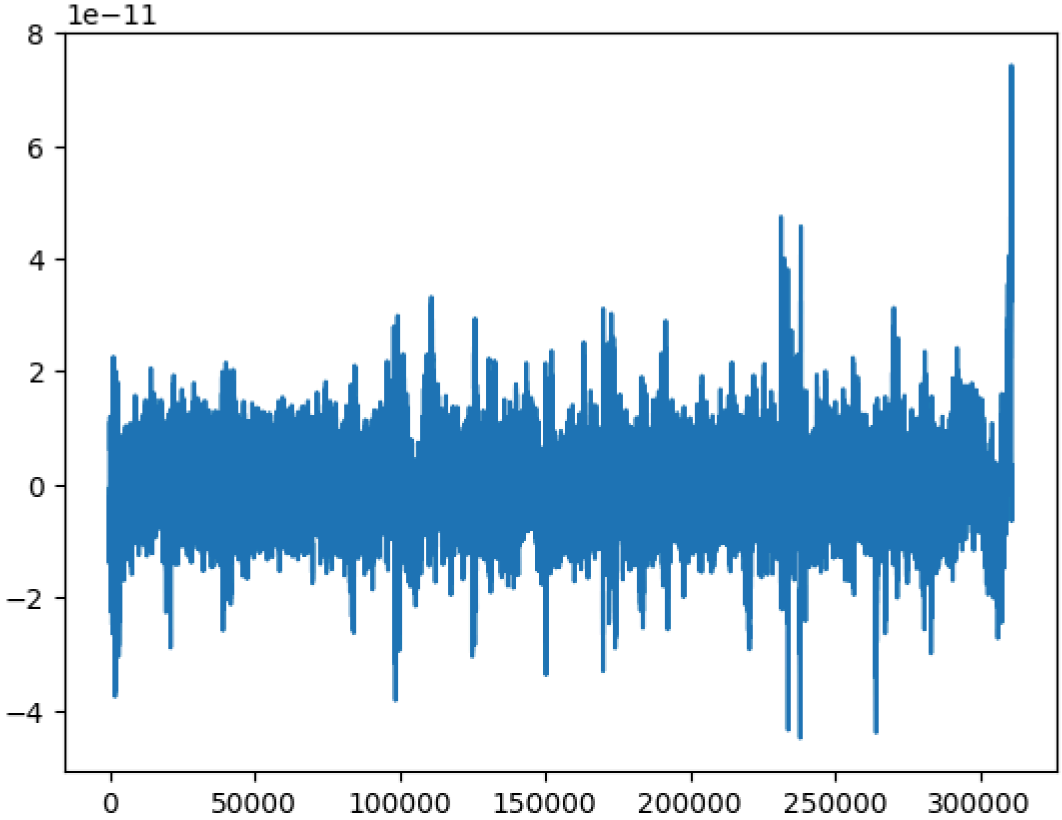


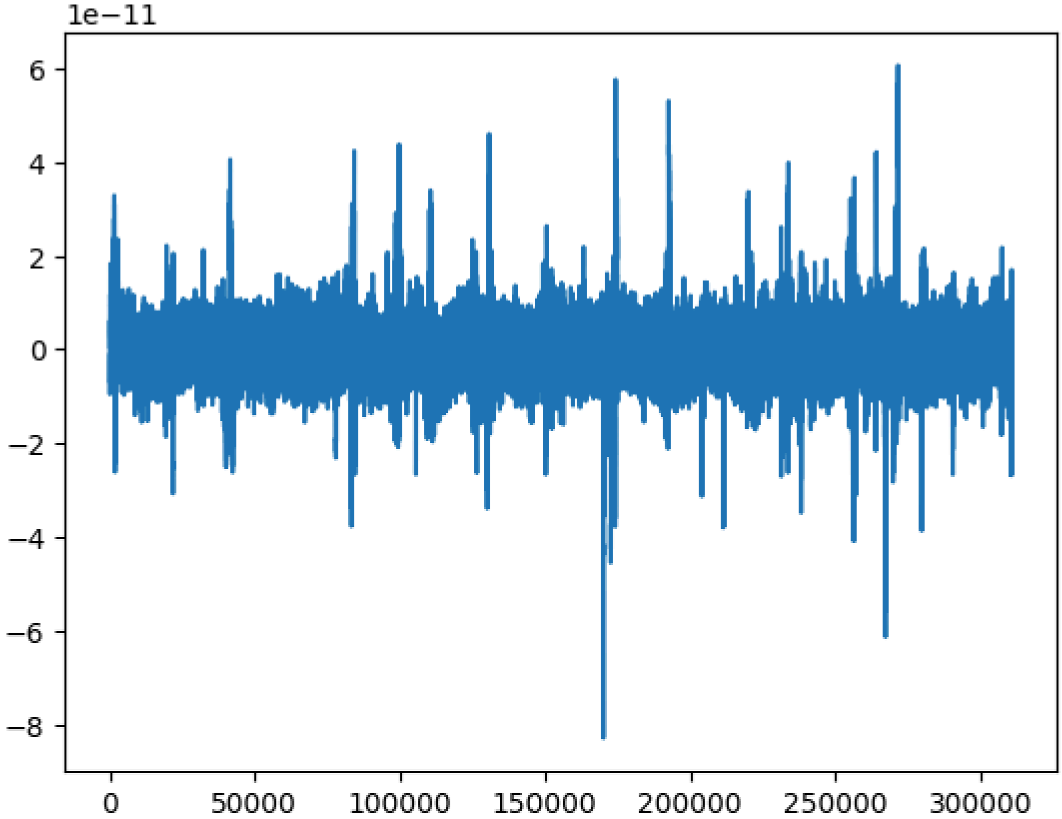


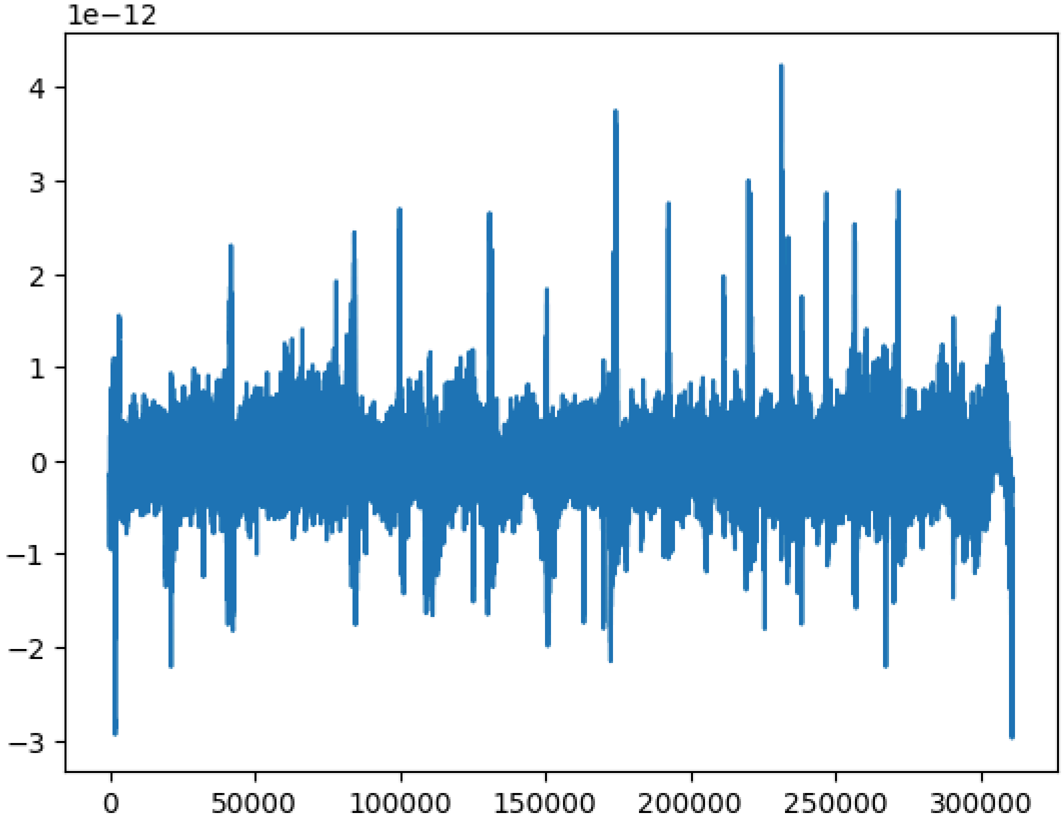
Check the data that was preprocessed, but not parceled

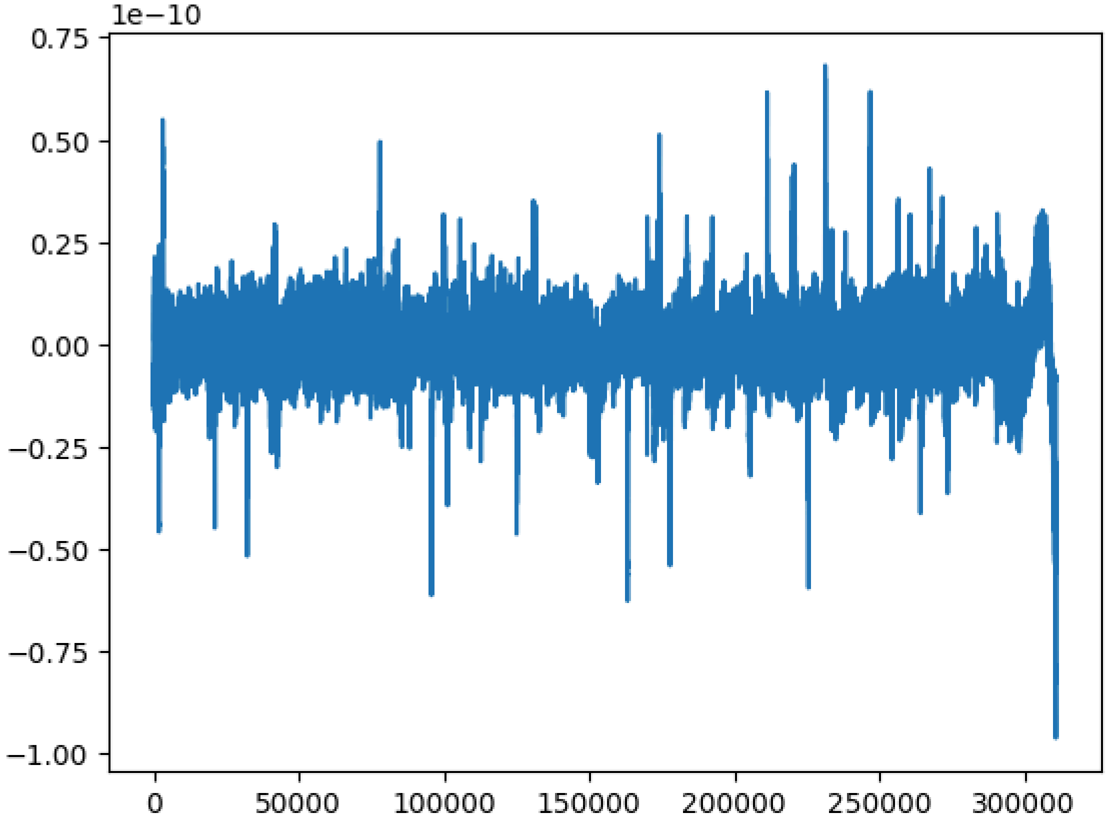
In [110…

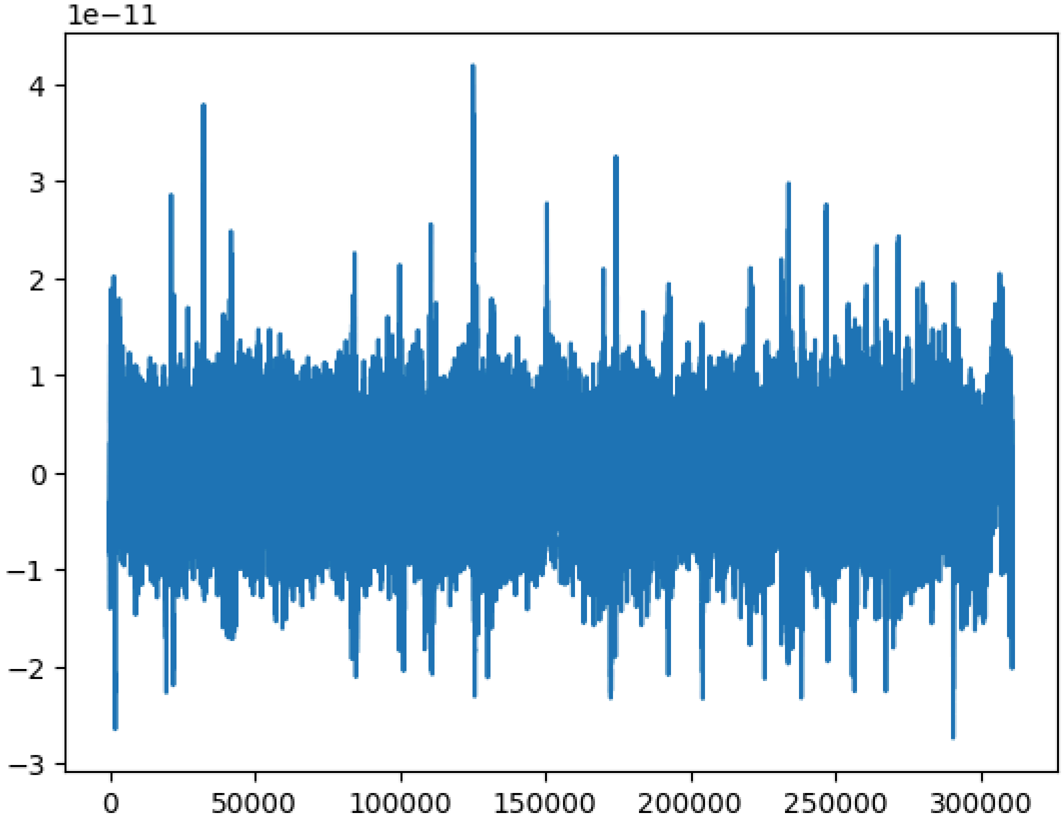
```
for i in range(10):
    plt.figure()
    plt.plot(preproc_MEG[i])
    plt.show()
```

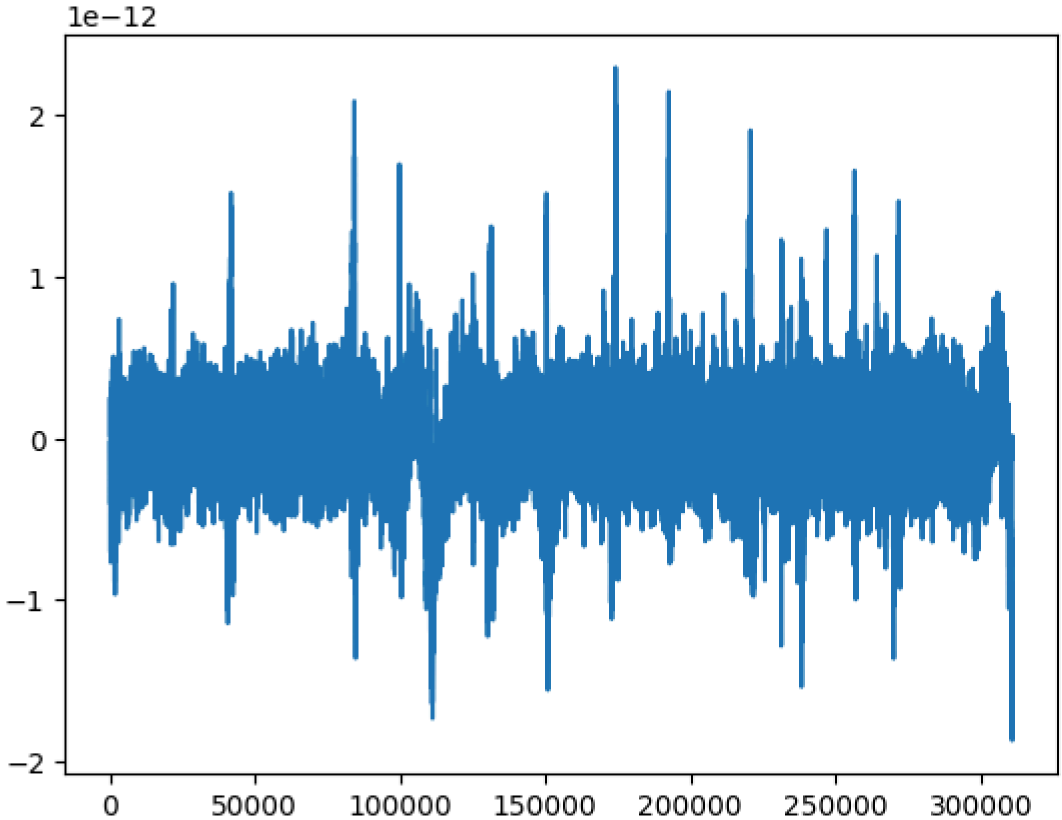

1e−11
8
6
4
2
0
−2
−4
0
50000
100000
150000
200000
250000
300000

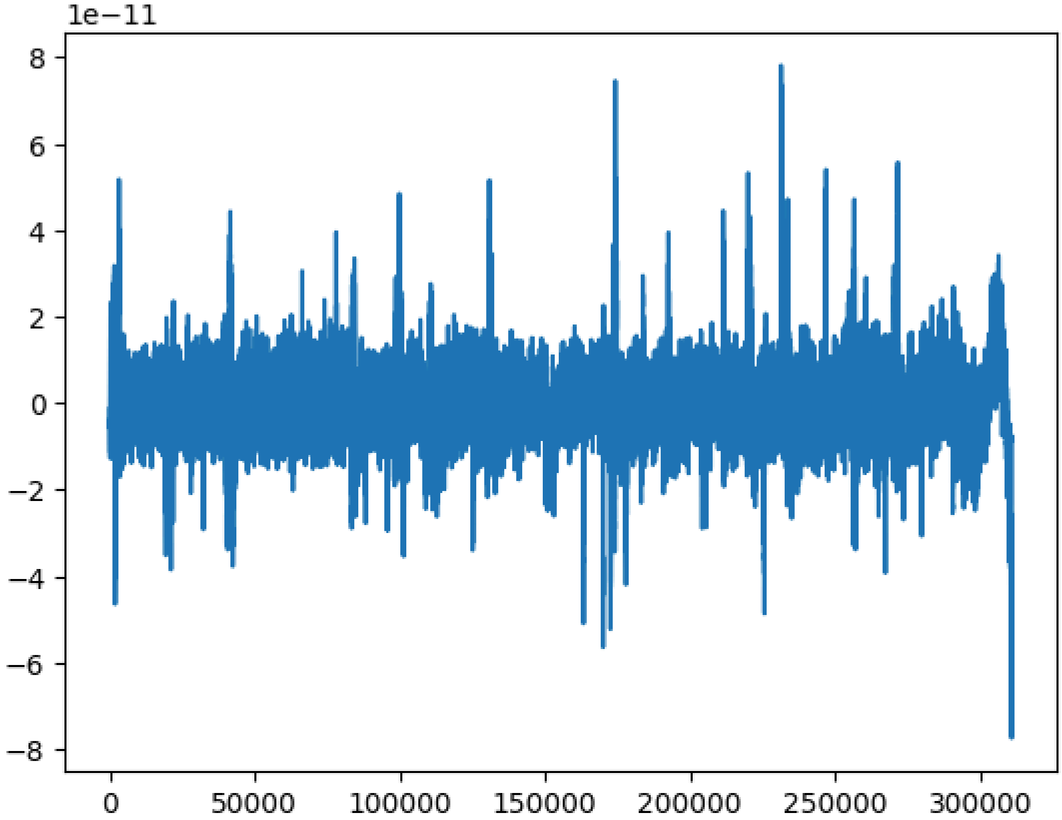

1e−11
6
4
2
0
−2
−4
−6
−8
0
50000
100000
150000
200000
250000
300000

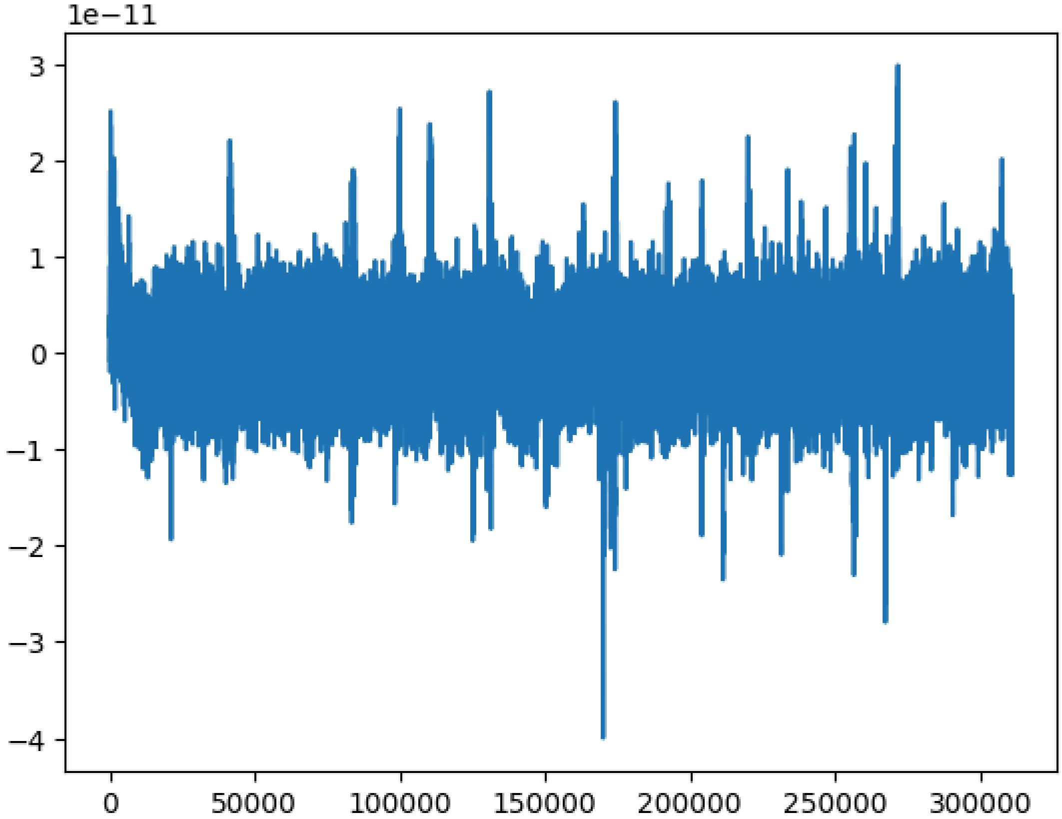

1e−12
4
3
2
1
0
−1
−2
−3
0
50000
100000
150000
200000
250000
300000

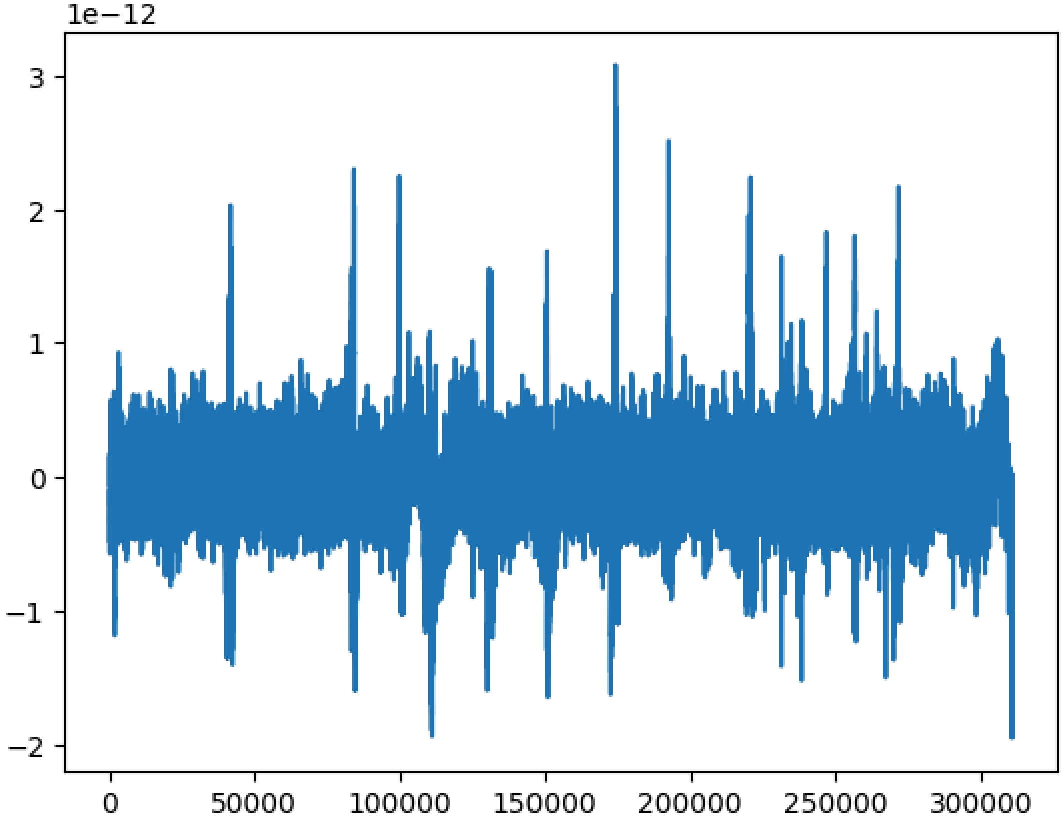

1e−10
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
50000
100000
150000
200000
250000
300000

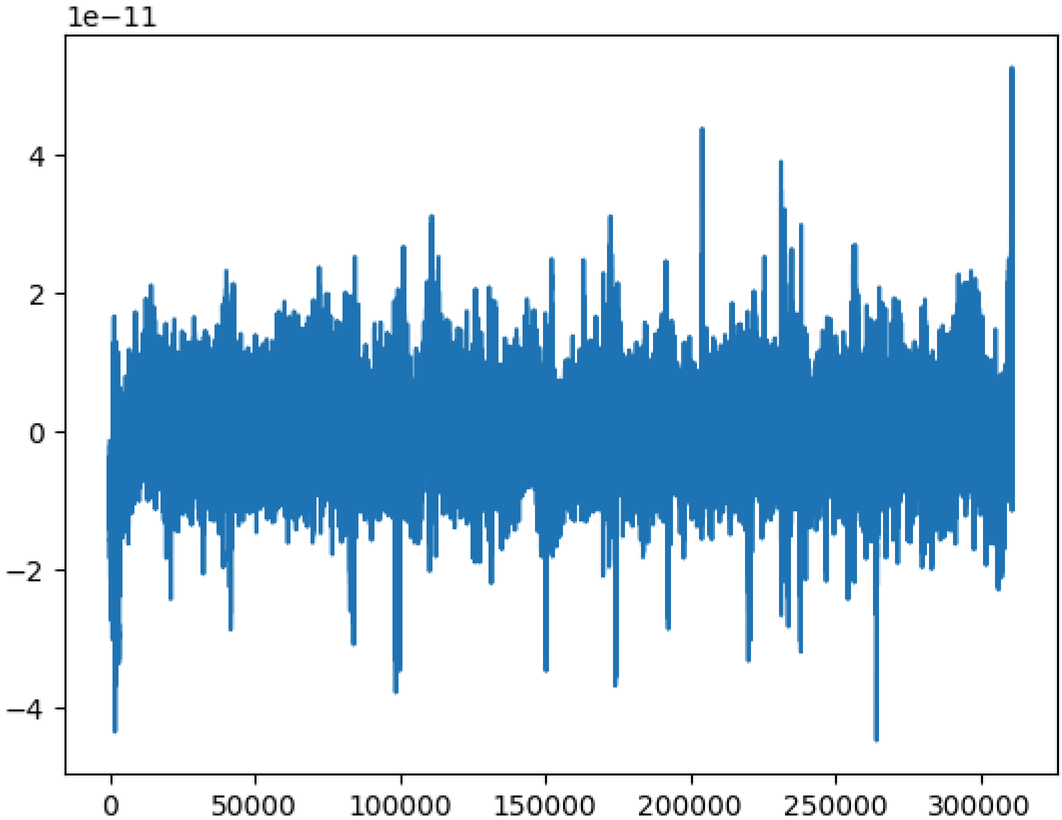

1e−11
4
3
2
1
0
−1
−2
−3
0
50000
100000
150000
200000
250000
300000


1e−12
2
1
0
−1
−2
0
50000
100000
150000
200000
250000
300000


1e−11
8
6
4
2
0
−2
−4
−6
−8
0
50000
100000
150000
200000
250000
300000

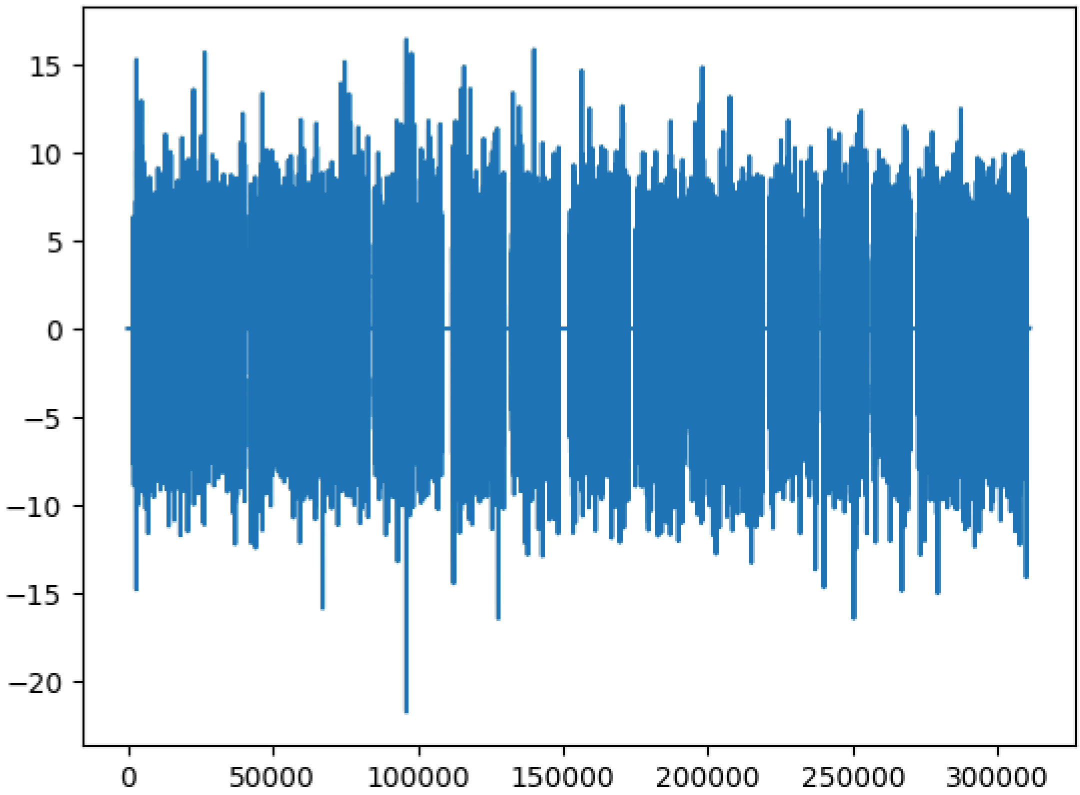

1e−11
3
2
1
0
−1
−2
−3
−4
0
50000
100000
150000
200000
250000
300000

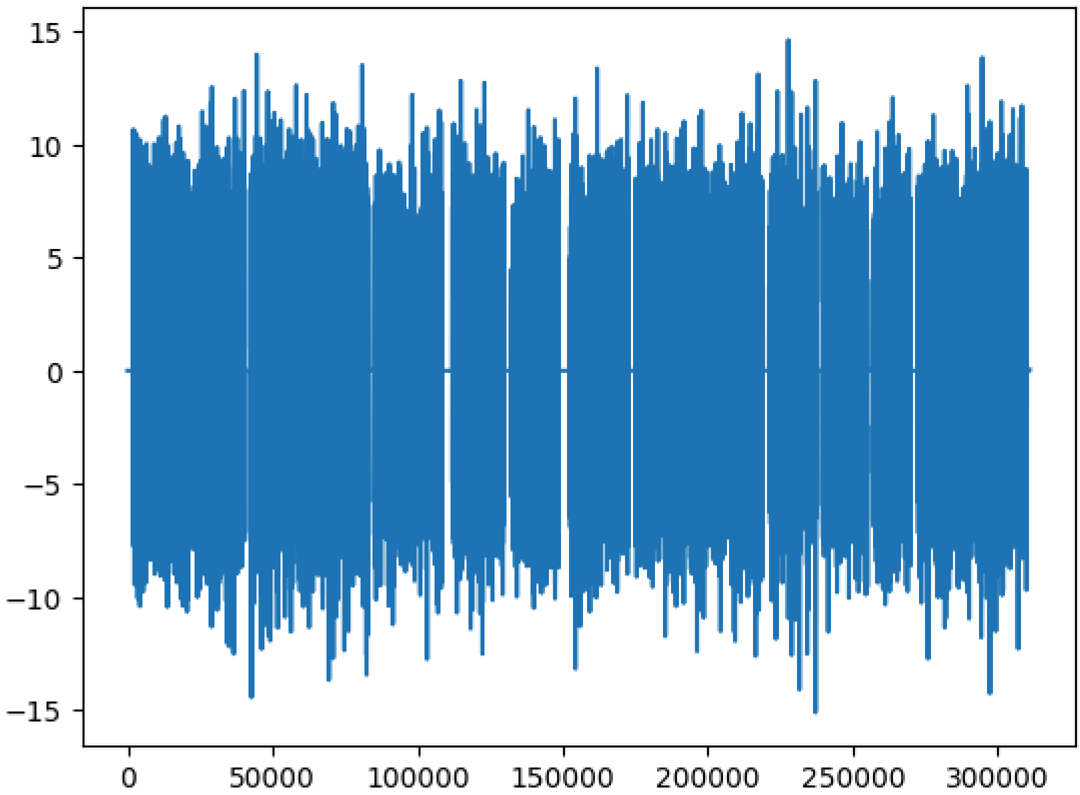


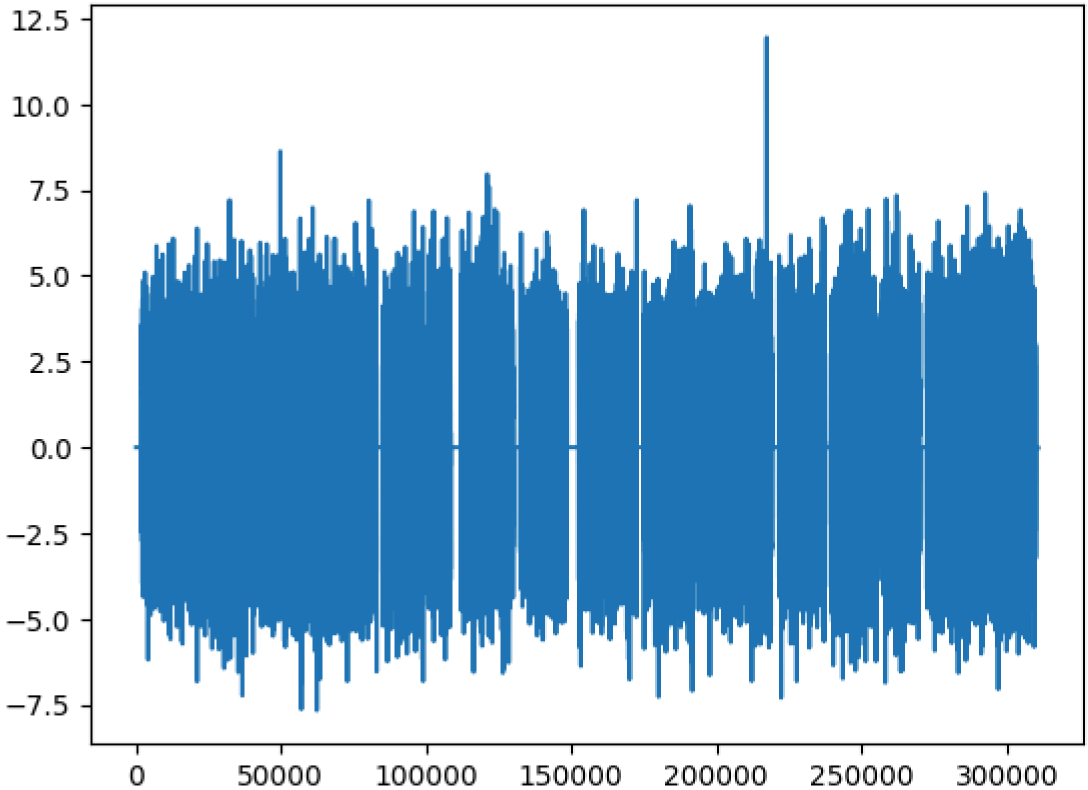


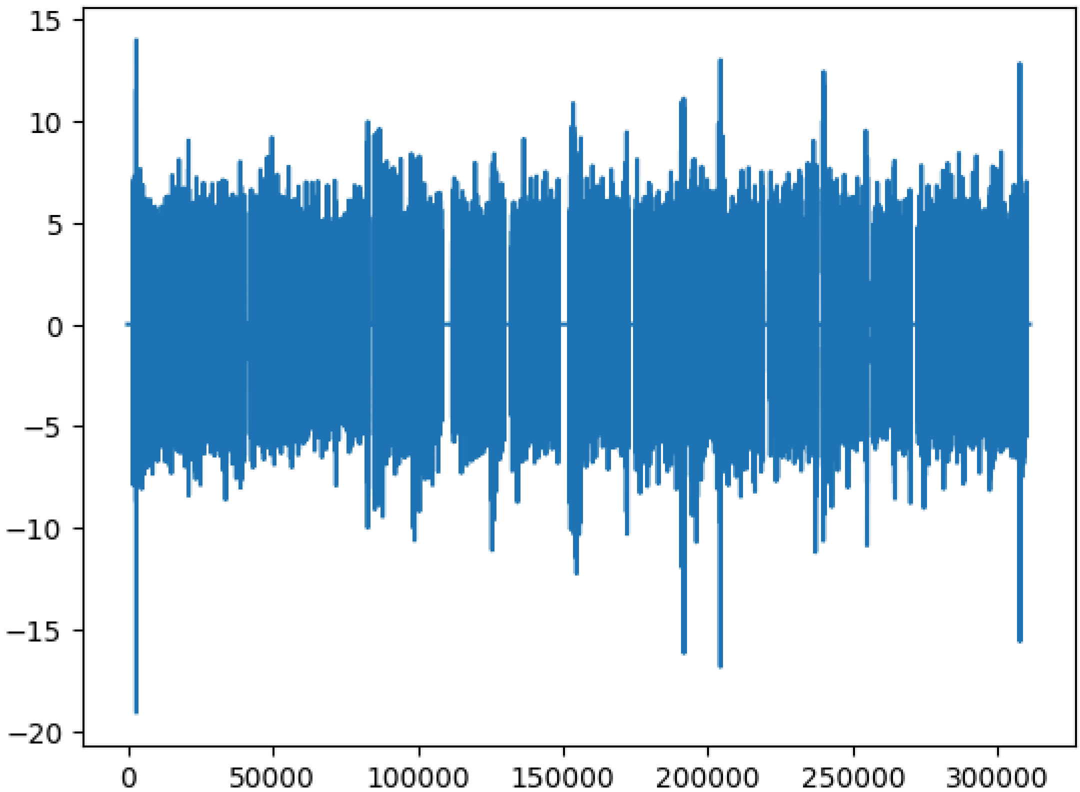
In [111…

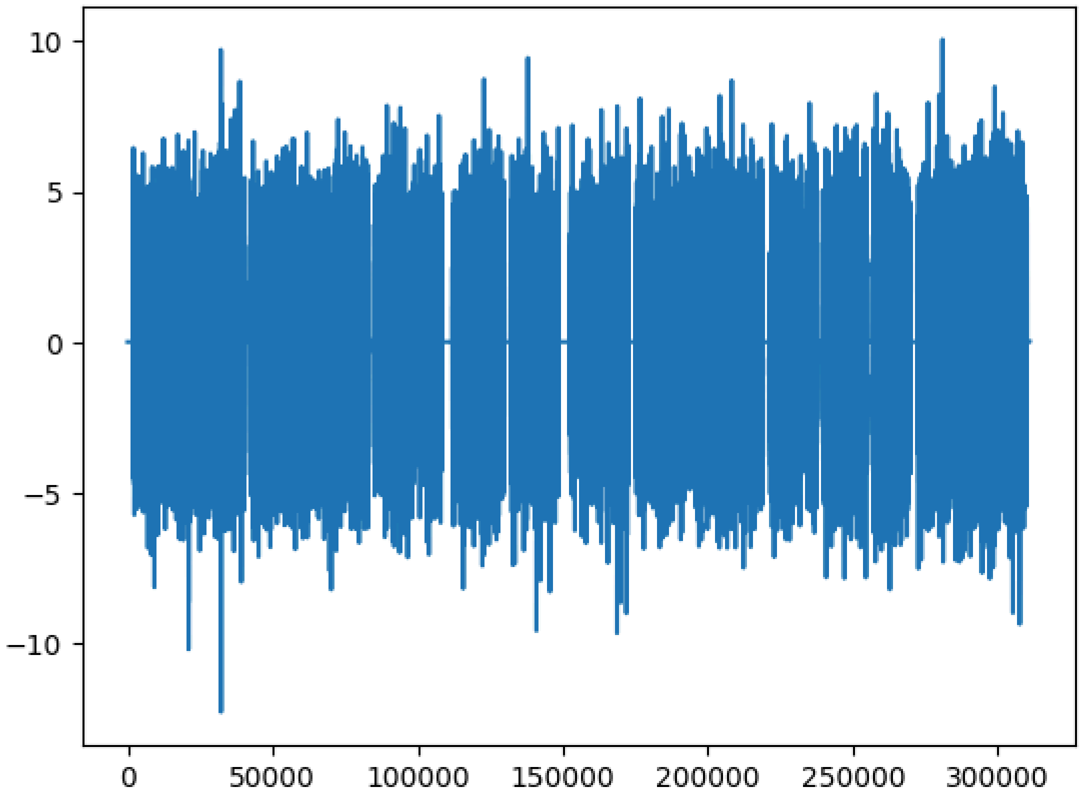
```
for i in range(5):
    plt.figure()
    plt.plot(toplot_MEG[i])
    plt.show()
```


15
10
5
0
−5
−10
−15
−20
0
50000
100000
150000
200000
250000
300000


15
10
5
0
−5
−10
−15
0
50000
100000
150000
200000
250000
300000


12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
0
50000
100000
150000
200000
250000
300000


15
10
5
0
−5
−10
−15
−20
0
50000
100000
150000
200000
250000
300000

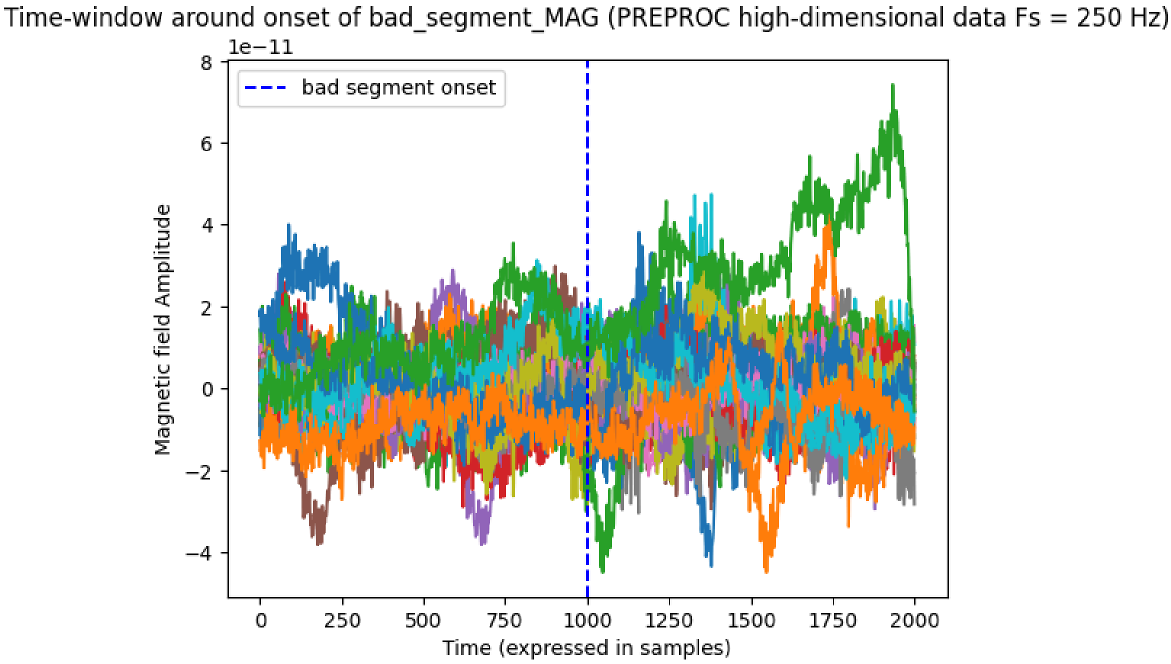


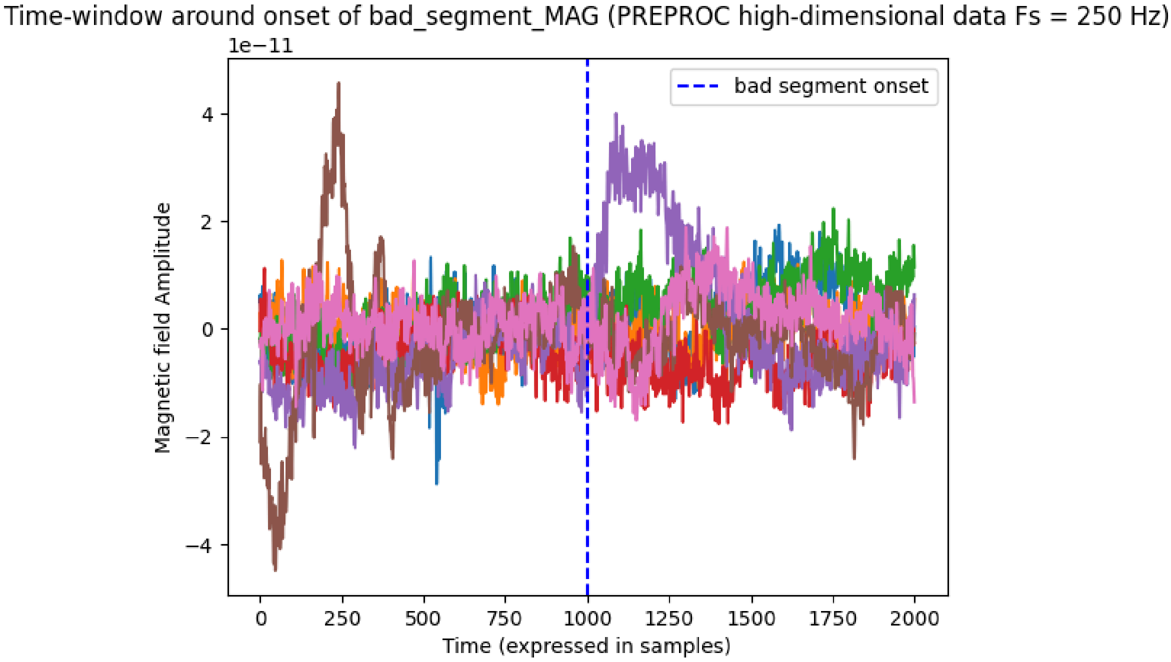
In [112…

```
preproc_MEG_raw = mne.io.read_raw_fif("/home/olivierb/processed_data/meg_094

preproc_MEG = preproc_MEG_raw.get_data()

# Get timepoints corresponding to the indices
bad_segment_mag_timepoints = annotations.onset[bad_segment_mag_idx]
bad_segment_grad_timepoints = annotations.onset[bad_segment_grad_idx]

bad_segment_mag_timepoints = [(timepoint - loaded.first_samp/250)*250 for ti
bad_segment_grad_timepoints = [(timepoint - loaded.first_samp/250)*250 for t

plt.figure()
for segment in range(len(bad_segment_mag_timepoints)):
    plt.plot(preproc_MEG[0][int(bad_segment_mag_timepoints[segment] - 1000):
plt.axvline(x = 1000, color = 'b', linestyle='dashed', label='bad segment or
plt.xlabel('Time (expressed in samples)')
plt.ylabel('Magnetic field Amplitude')
plt.title('Time-window around onset of bad_segment_MAG (PREPROC high-dimensi
plt.legend()

plt.figure()
for segment in range(len(bad_segment_grad_timepoints)):
    plt.plot(preproc_MEG[0][int(bad_segment_grad_timepoints[segment] - 1000)
plt.axvline(x = 1000, color = 'b', linestyle='dashed', label='bad segment or
plt.xlabel('Time (expressed in samples)')
plt.ylabel('Magnetic field Amplitude')
plt.title('Time-window around onset of bad_segment_MAG (PREPROC high-dimensi
plt.legend()
```

Out[112]:

```
<matplotlib.legend.Legend at 0x7efc01ab3280>
```





Do the SAME but for **completely raw data** (because now the bad segment is simply flattened out for some reason? For 500 samples (which aligns with the **segment_len** parameter of 500 given in the preprocessing)

relevant piece of code: def detect_artefacts in osl/preprocessing/osl_wrappers.py

In [82]:
```
raw_data = raw_dataset_dir = mne.io.read_raw_fif("/home/data/vub_ms/MEGDATA_
raw_data.info

print(np.shape(raw_data.get_data()))
print(np.shape(loaded.get_data()))
```

```
Opening raw data file /home/data/vub_ms/MEGDATA_ANA/SDMT/DATA/meg_0945_SD
MT_tsss_mc.fif...
    Range : 132000 ... 1375999 =    132.000 ...  1375.999 secs
Ready.
```

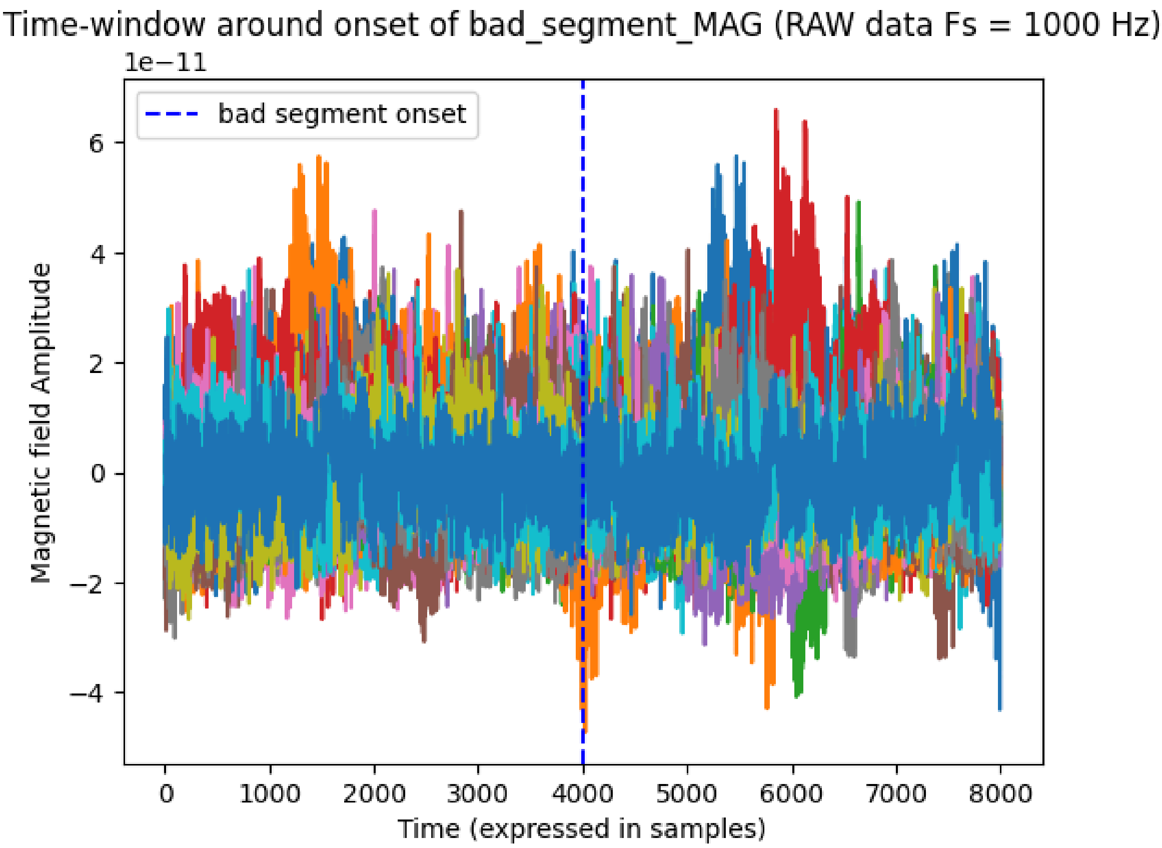
```
/tmp/ipykernel_2107657/1702676105.py:1: RuntimeWarning: This filename (/h
ome/data/vub_ms/MEGDATA_ANA/SDMT/DATA/meg_0945_SDMT_tsss_mc.fif) does not
conform to MNE naming conventions. All raw files should end with raw.fif,
raw_sss.fif, raw_tsss.fif, _meg.fif, _eeg.fif, _ieeg.fif, raw.fif.gz, raw
_sss.fif.gz, raw_tsss.fif.gz, _meg.fif.gz, _eeg.fif.gz or _ieeg.fif.gz
  raw_data = raw_dataset_dir = mne.io.read_raw_fif("/home/data/vub_ms/MEG
DATA_ANA/SDMT/DATA/meg_0945_SDMT_tsss_mc.fif")
(333, 1244000)
(38, 311000)
```

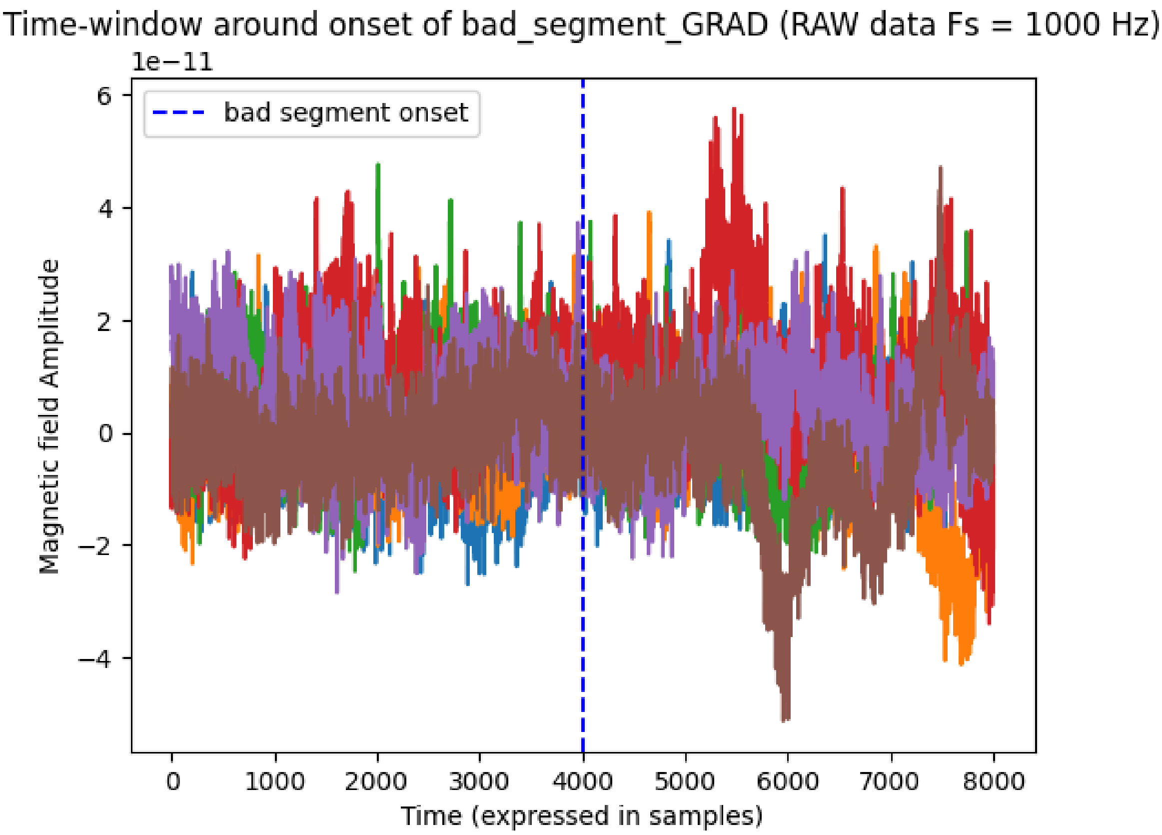
In [97]:

```python
raw_MEG = raw_data.get_data()

# Get timepoints corresponding to the indices
bad_segment_mag_timepoints = annotations.onset[bad_segment_mag_idx]
bad_segment_grad_timepoints = annotations.onset[bad_segment_grad_idx]

bad_segment_mag_timepoints = [(timepoint - loaded.first_samp/1000.0)*1000 fo
bad_segment_grad_timepoints = [(timepoint - loaded.first_samp/1000.0)*1000 f


plt.figure()
for segment in range(len(bad_segment_mag_timepoints)):
    plt.plot(raw_MEG[0][int(bad_segment_mag_timepoints[segment] - 4000):int(
plt.axvline(x = 4000, color = 'b', linestyle='dashed', label='bad segment or
plt.xlabel('Time (expressed in samples)')
plt.ylabel('Magnetic field Amplitude')
plt.title('Time-window around onset of bad_segment_MAG (RAW data Fs = 1000 H
plt.legend()

plt.figure()
for segment in range(len(bad_segment_grad_timepoints)):
    plt.plot(raw_MEG[0][int(bad_segment_grad_timepoints[segment] - 4000):int
plt.axvline(x = 4000, color = 'b', linestyle='dashed', label='bad segment or
plt.xlabel('Time (expressed in samples)')
plt.ylabel('Magnetic field Amplitude')
plt.title('Time-window around onset of bad_segment_GRAD (RAW data Fs = 1000 
plt.legend()
```

Out[97]:

```
<matplotlib.legend.Legend at 0x7efcf04a0b50>
```





1. Summary statistics

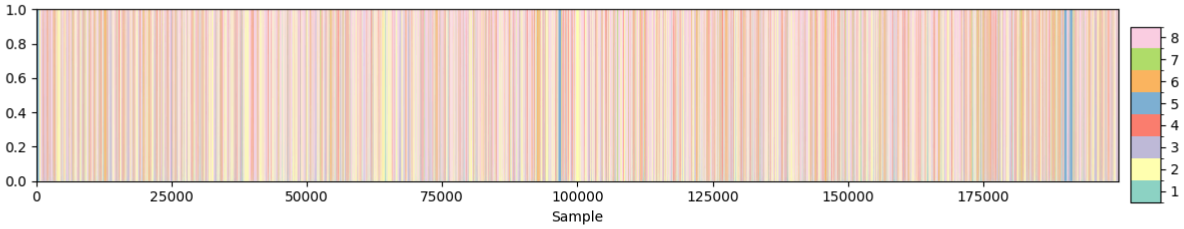
1. Fractional occupacy
2. Mean lifetime
3. Mean interval
4. Switching rate

5. Group comparisons (on the 4 summary metrics)

Plot raw alpha timecourse

In [20]:
```
from osl_dynamics.utils import plotting

# Plot the state probability time course for the 1st subject (and a limited
plotting.plot_alpha(alpha[0], n_samples=200000)
```

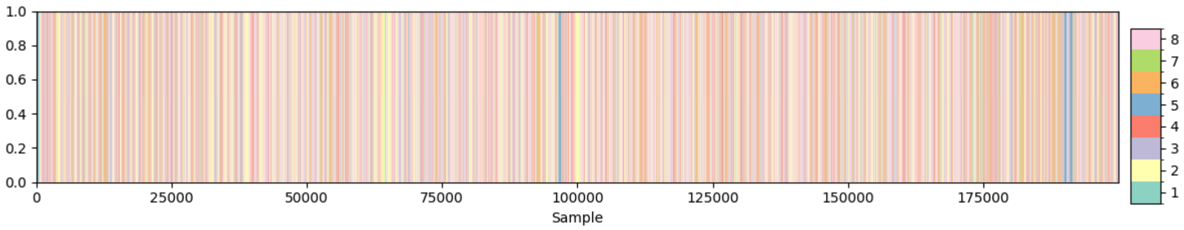
Out[20]:
```
(<Figure size 1200x250 with 2 Axes>, [<Axes: xlabel='Sample'>])
```



Enforce 1 state per timepoint (argmax)

In [21]:
```
from osl_dynamics.inference import modes

# Hard classify the state probabilities (needed before you calculate summary
stc = modes.argmax_time_courses(alpha)

# Plot the state time course for the first subject (8 seconds)
plotting.plot_alpha(stc[0], n_samples=200000)
```

Out[21]:
```
(<Figure size 1200x250 with 2 Axes>, [<Axes: xlabel='Sample'>])
```



1.1 Fractional occupacy

In [22]:
```
# Calculate fractional occupancies
fo = modes.fractional_occupancies(stc)
print(fo.shape)
print('subjects', 'amount_states')
```

```
(110, 8)
subjects amount_states
```

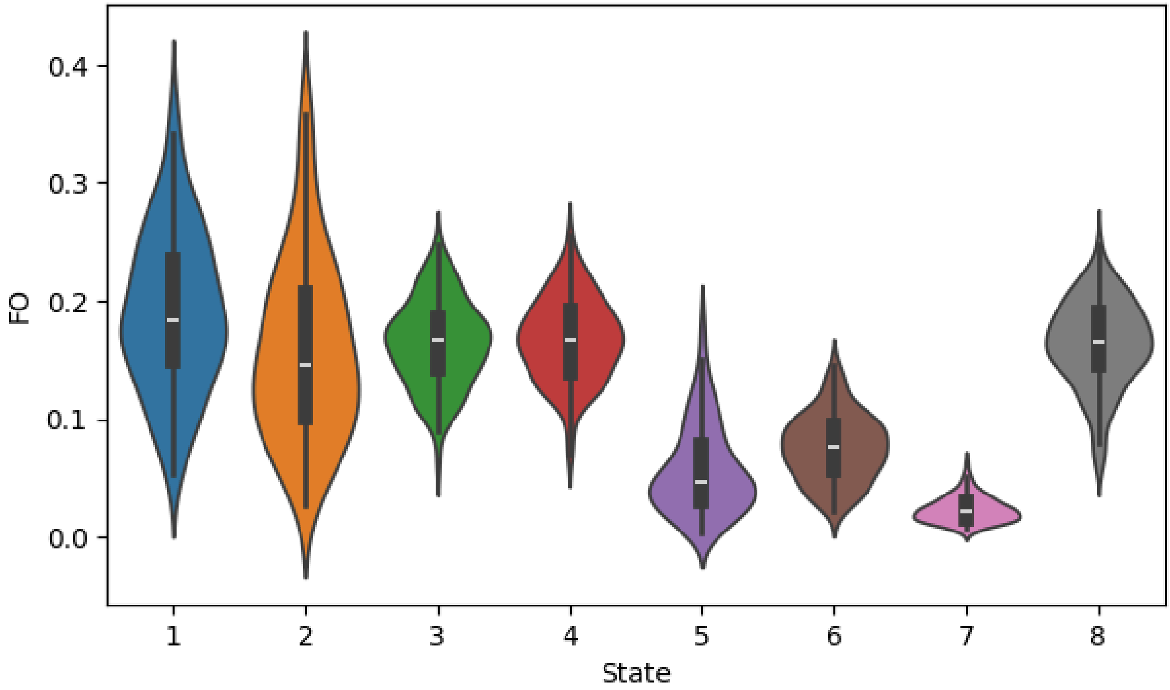
In [23]:
```
## Print the GROUP AVERAGE (all subjects) Fractional Occupancy
print(np.mean(fo, axis=0))
```

```
[0.19032232 0.1582407  0.16413614 0.16720963 0.05694389 0.07589035
 0.02355835 0.16369861]
```

In [24]:
```
# Plot the distribution of fractional occupancy (FO) across subjects (violin
plotting.plot_violin(fo.T, x_label="State", y_label="FO")
```

```
2024-05-06 09:53:33 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
2024-05-06 09:53:33 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
```

Out[24]:
```
(<Figure size 700x400 with 1 Axes>, <Axes: xlabel='State', ylabel='FO'>)
```



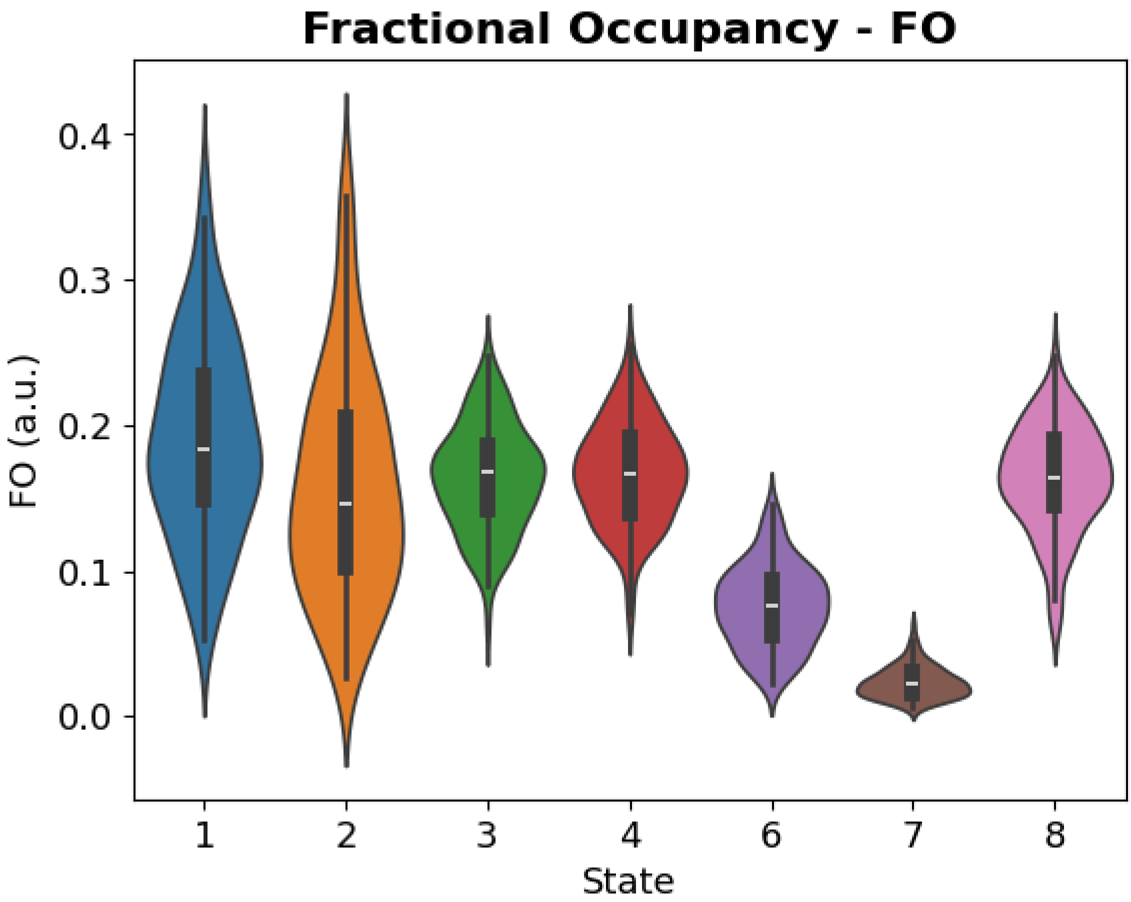
In [26]:
```
print(fo[:][:, np.array([True, True, True, True, False, True, True, True])].
```

```
(110, 7)
```

In [27]:
```
labels=['1', '2', '3', '4', '6', '7', '8']
fo_new = fo[:][:, np.array([True, True, True, True, False, True, True, True]
ax = sns.violinplot(fo_new)
ax.set_xticklabels(labels, fontsize=13)
ax.set_yticklabels(ax.get_yticklabels(), fontsize=13)
ax.set_xlabel('State', fontsize=13)
ax.set_ylabel('FO (a.u.)', fontsize=13)
ax.set_title('Fractional Occupancy - FO', fontsize=16, weight='bold')
```

```
2024-05-06 09:55:55 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
2024-05-06 09:55:55 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
/tmp/ipykernel_2243037/2936777808.py:4: UserWarning: set_ticklabels() sho
uld only be used with a fixed number of ticks, i.e. after set_ticks() or
using a FixedLocator.
  ax.set_xticklabels(labels, fontsize=13)
/tmp/ipykernel_2243037/2936777808.py:5: UserWarning: set_ticklabels() sho
uld only be used with a fixed number of ticks, i.e. after set_ticks() or
using a FixedLocator.
  ax.set_yticklabels(ax.get_yticklabels(), fontsize=13)
```

Out[27]:
```
Text(0.5, 1.0, 'Fractional Occupancy - FO')
```

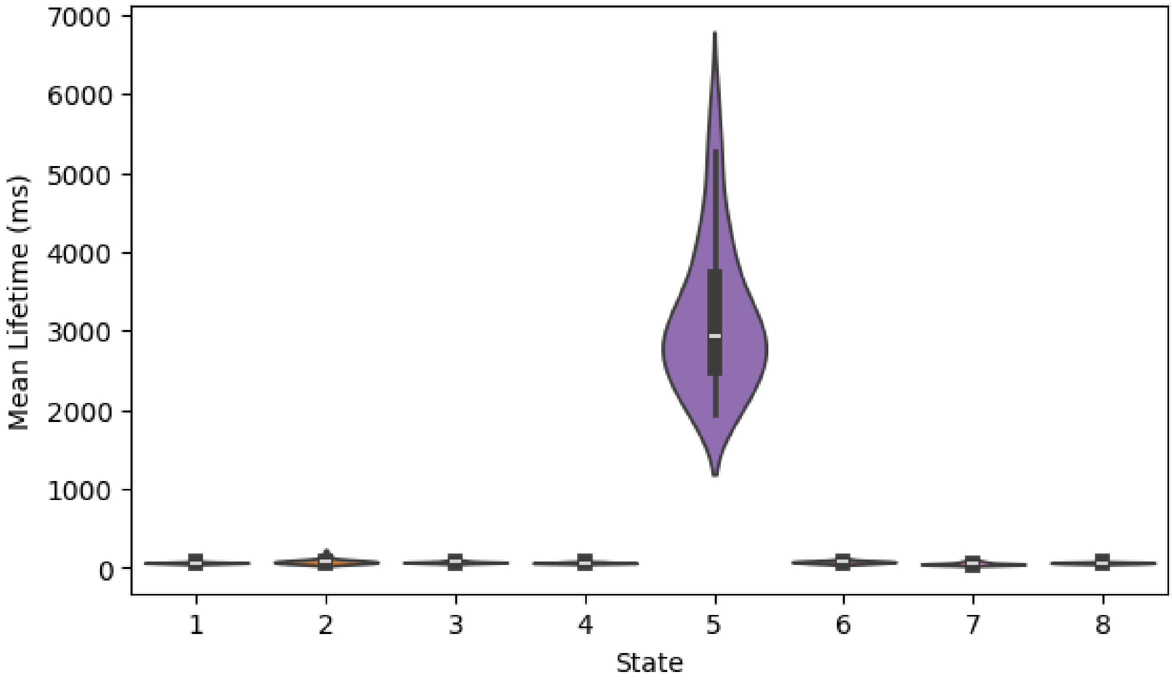


1.2 Mean lifetime

In [28]:
```
# Calculate mean lifetimes (in seconds)
mlt = modes.mean_lifetimes(stc, sampling_frequency=250)

# Convert to ms
mlt *= 1000

# Print the group average
print(np.mean(mlt, axis=0))

# Plot distribution across subjects
plotting.plot_violin(mlt.T, x_label="State", y_label="Mean Lifetime (ms)")
```

```
2024-05-06 09:56:08 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
2024-05-06 09:56:08 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
[  65.03354747   82.68635662   72.87268574   65.08896335 3177.90233214
   75.92202364   54.79349408   63.374315  ]
```

Out[28]:
```
(<Figure size 700x400 with 1 Axes>,
 <Axes: xlabel='State', ylabel='Mean Lifetime (ms)'>)
```



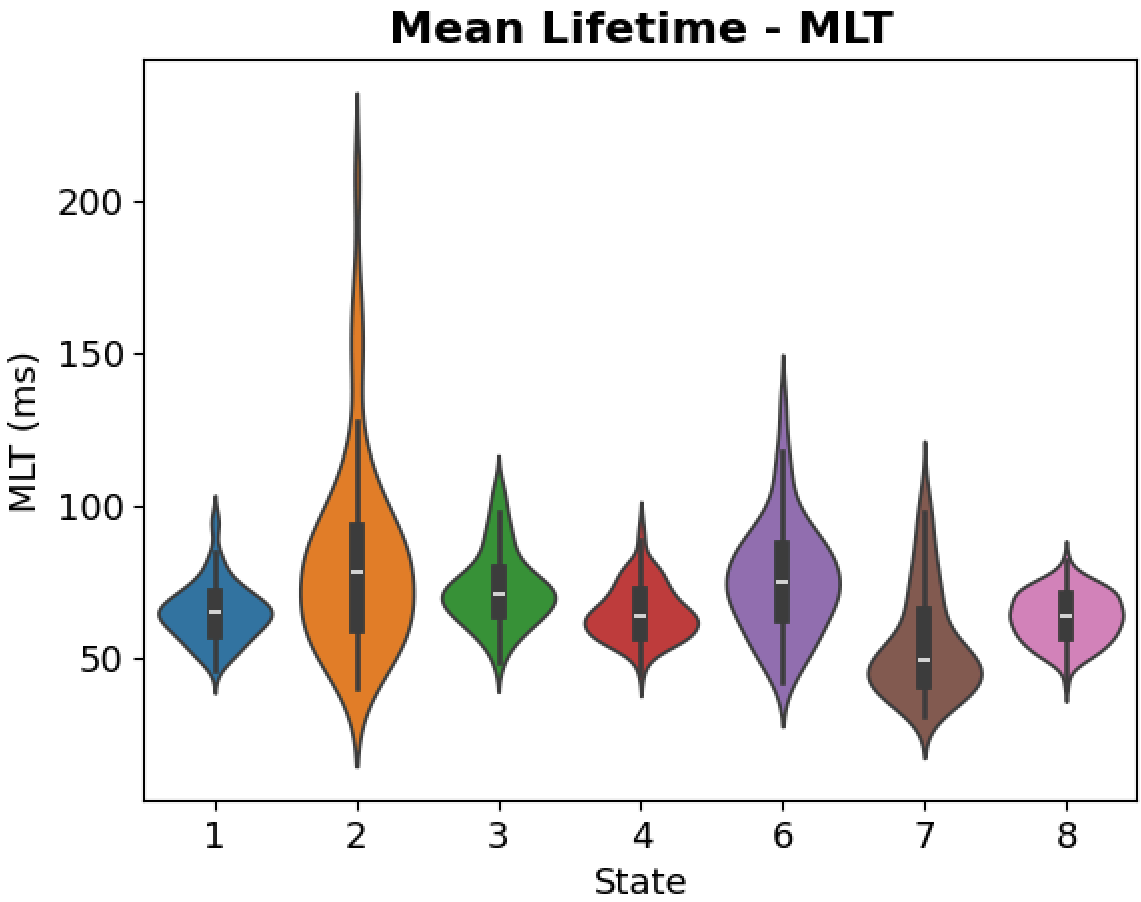
In [29]:

```
labels=['1', '2', '3', '4', '6', '7', '8']
mlt_new = mlt[:][:, np.array([True, True, True, True, False, True, True, Tru
ax = sns.violinplot(mlt_new)
ax.set_xticklabels(labels, fontsize=13)
ax.set_yticklabels(ax.get_yticklabels(), fontsize=13)
ax.set_xlabel('State', fontsize=13)
ax.set_ylabel('MLT (ms)', fontsize=13)
ax.set_title('Mean Lifetime - MLT', fontsize=16, weight='bold')
```

```
2024-05-06 09:56:28 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
2024-05-06 09:56:28 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
/tmp/ipykernel_2243037/3211227311.py:4: UserWarning: set_ticklabels() sho
uld only be used with a fixed number of ticks, i.e. after set_ticks() or
using a FixedLocator.
  ax.set_xticklabels(labels, fontsize=13)
/tmp/ipykernel_2243037/3211227311.py:5: UserWarning: set_ticklabels() sho
uld only be used with a fixed number of ticks, i.e. after set_ticks() or
using a FixedLocator.
  ax.set_yticklabels(ax.get_yticklabels(), fontsize=13)
```

Out[29]:

```
Text(0.5, 1.0, 'Mean Lifetime - MLT')
```

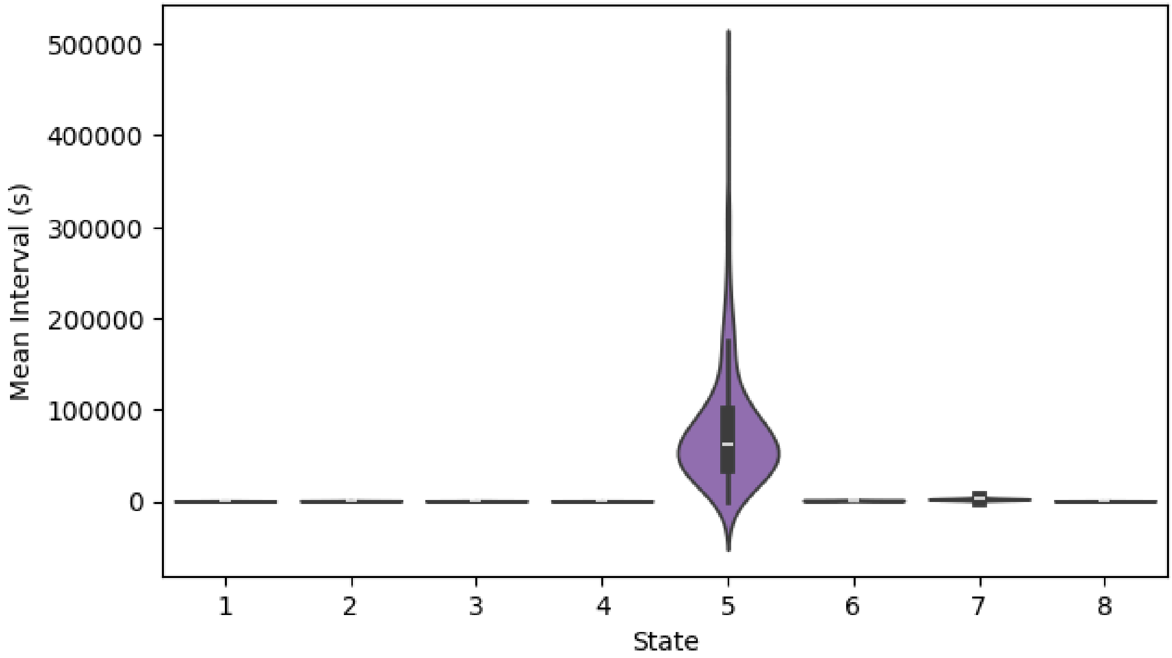


1.3 Mean interval

In [30]:
```
# Calculate mean intervals (in seconds)
mintv = modes.mean_intervals(stc, sampling_frequency=250)

# Convert to ms
mintv *= 1000

# Print the group average
print(np.mean(mintv, axis=0))

# Plot distribution across subjects
plotting.plot_violin(mintv.T, x_label="State", y_label="Mean Interval (s)")
```

```
2024-05-06 09:56:42 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
2024-05-06 09:56:42 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
[  309.44190629   493.53052413   376.97353045   330.83247609
 79165.07227981   984.96669495  2533.47711865   332.70825644]
```

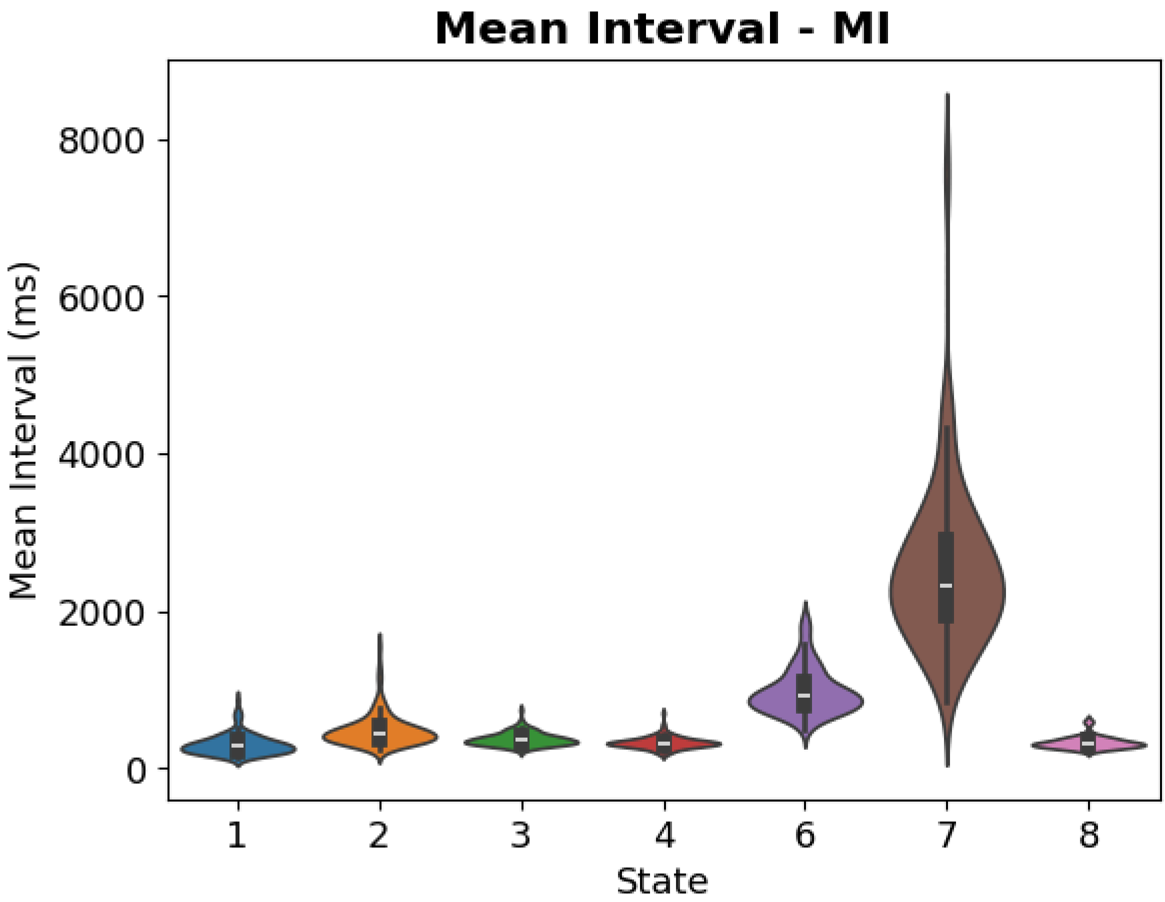
Out[30]:
```
(<Figure size 700x400 with 1 Axes>,
 <Axes: xlabel='State', ylabel='Mean Interval (s)'>)
```



In [31]:
```
labels=['1', '2', '3', '4', '6', '7', '8']
mintv_new = mintv[:][:, np.array([True, True, True, True, False, True, True,
ax = sns.violinplot(mintv_new)
ax.set_xticklabels(labels, fontsize=13)
ax.set_yticklabels(ax.get_yticklabels(), fontsize=13)
ax.set_xlabel('State', fontsize=13)
ax.set_ylabel('Mean Interval (ms)', fontsize=13)
ax.set_title('Mean Interval - MI', fontsize=16, weight='bold')
```

```
2024-05-06 09:57:00 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
2024-05-06 09:57:00 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
/tmp/ipykernel_2243037/2460597851.py:4: UserWarning: set_ticklabels() sho
uld only be used with a fixed number of ticks, i.e. after set_ticks() or
using a FixedLocator.
  ax.set_xticklabels(labels, fontsize=13)
/tmp/ipykernel_2243037/2460597851.py:5: UserWarning: set_ticklabels() sho
uld only be used with a fixed number of ticks, i.e. after set_ticks() or
using a FixedLocator.
  ax.set_yticklabels(ax.get_yticklabels(), fontsize=13)
```

Out[31]:
```
Text(0.5, 1.0, 'Mean Interval - MI')
```

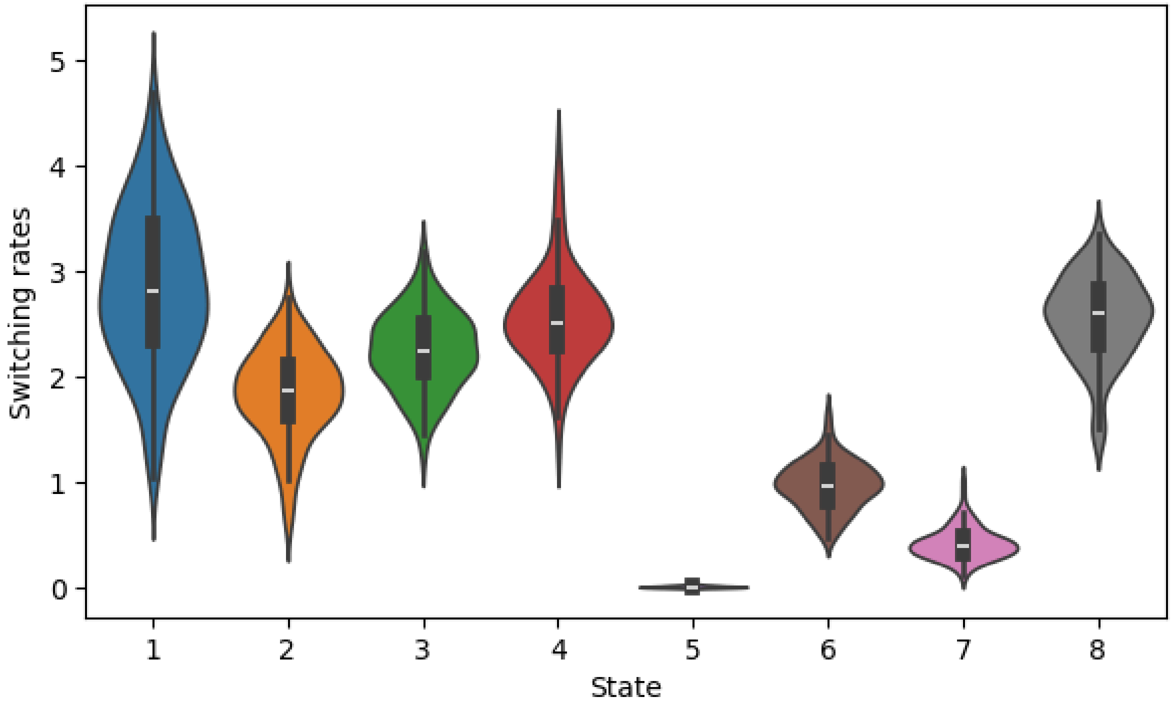


1.4 Switching rates

In [32]:
```
sw_rate = modes.switching_rates(stc, sampling_frequency=250)

# Print the group average
print(np.mean(sw_rate, axis=0))

# Plot distribution across subjects
plotting.plot_violin(sw_rate.T, x_label="State", y_label="Switching rates")
```

```
2024-05-06 09:57:18 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
2024-05-06 09:57:18 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
[2.86095887 1.84392572 2.25588314 2.57264923 0.01665417 0.98023773
 0.42996577 2.56510178]
```

Out[32]:
```
(<Figure size 700x400 with 1 Axes>,
 <Axes: xlabel='State', ylabel='Switching rates'>)
```



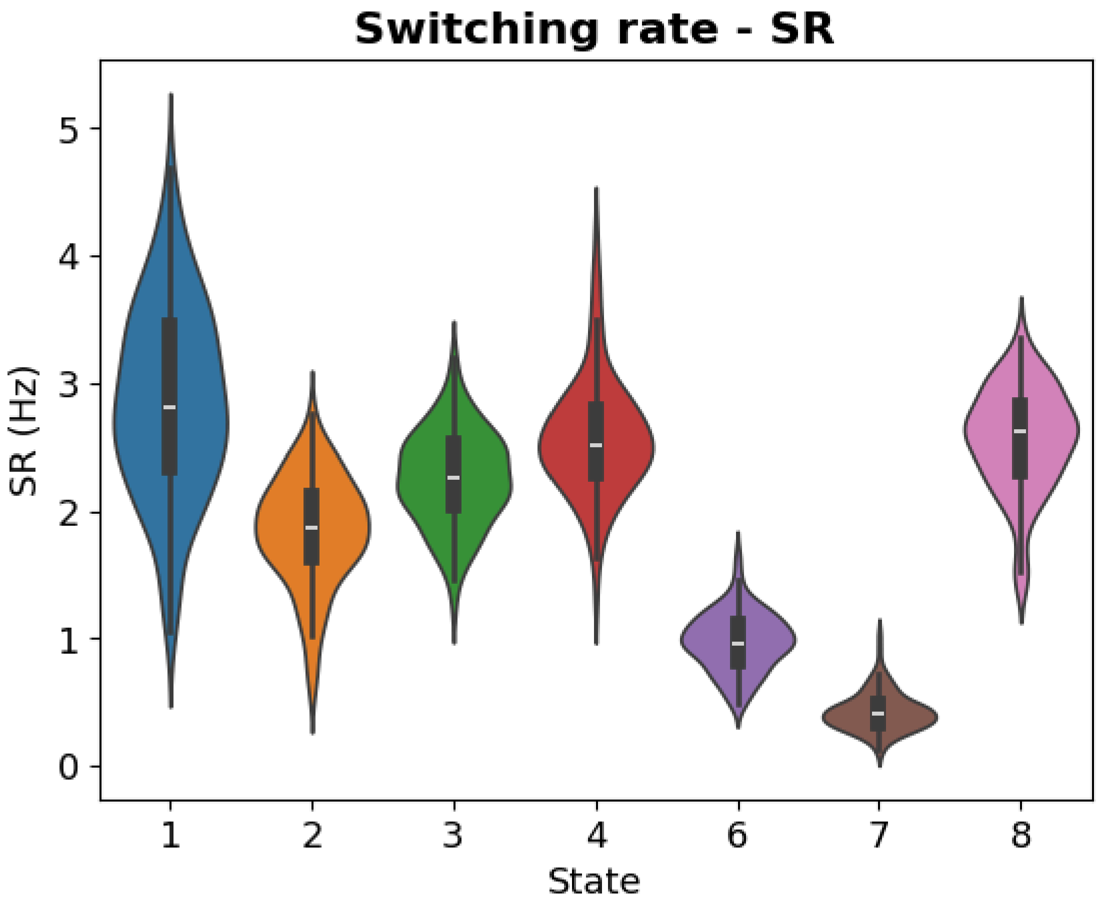
In [33]:

```
labels=['1', '2', '3', '4', '6', '7', '8']
sw_rate_new = sw_rate[:][:, np.array([True, True, True, True, False, True, T
ax = sns.violinplot(sw_rate_new)
ax.set_xticklabels(labels, fontsize=13)
ax.set_yticklabels(ax.get_yticklabels(), fontsize=13)
ax.set_xlabel('State', fontsize=13)
ax.set_ylabel('SR (Hz)', fontsize=13)
ax.set_title('Switching rate - SR', fontsize=16, weight='bold')
```

```
2024-05-06 09:57:37 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
2024-05-06 09:57:37 INFO matplotlib.category [category.py:223:update]: Us
ing categorical units to plot a list of strings that are all parsable as
floats or dates. If these strings should be plotted as numbers, cast to t
he appropriate data type before plotting.
/tmp/ipykernel_2243037/3637999492.py:4: UserWarning: set_ticklabels() sho
uld only be used with a fixed number of ticks, i.e. after set_ticks() or
using a FixedLocator.
  ax.set_xticklabels(labels, fontsize=13)
/tmp/ipykernel_2243037/3637999492.py:5: UserWarning: set_ticklabels() sho
uld only be used with a fixed number of ticks, i.e. after set_ticks() or
using a FixedLocator.
  ax.set_yticklabels(ax.get_yticklabels(), fontsize=13)
```

Out[33]:

```
Text(0.5, 1.0, 'Switching rate - SR')
```



1.5 Group comparisons

HC vs. MS

First you need to extract groups (HC/MS)

In [34]:
```
## First we split the subjects into 2 groups based on the 'subjectinfo.mat'

# Need subject_IDs_group_analysis

from scipy.io import loadmat
import pandas as pd
import numpy as np

def patientinfo_to_df(patientinfo_mat_path):

    array = loadmat(patientinfo_mat_path)['subjectinfo'][0]

    indices_relevant_cols = [0,3,4,5,6,7,16,19,21,26]
    relevant_col_names = ['code', 'disdur', 'type', 'age', 'edu', 'SDMT', 'g

    # for each of the relevant columns
    extracted_out = []
    for column in range(len(indices_relevant_cols)):
        extracted_col = [array[patient][indices_relevant_cols[column]] for p
        extracted_out.append(extracted_col)

    df_out = pd.DataFrame()
    for col in range(len(indices_relevant_cols)):
        df_out[relevant_col_names[col]] = extracted_out[col]
```

```
    # Recursively unpack value from nested arrays
    def unpack_nested(val):
        if isinstance(val, np.ndarray):
            return unpack_nested(val[0])
        else:
            return val

    df_out = df_out.map(unpack_nested)

    return df_out
```

In [35]:
```
df_patientinfo = patientinfo_to_df("/home/olivierb/Downloads/subjectinfo.mat
from IPython.display import display

# Get only 110 subjects for which we have both succesful parceled MEG data &
filtered_df = df_patientinfo[df_patientinfo['code'].isin(subject_IDs_group_a

# Get all row indices with isms = 0 ==> healthy controls
df_control_idx = filtered_df.index[filtered_df['isms'] == 0].tolist()
#print(df_control_idx)
print(len(df_control_idx))

# Get all row indices with isms = 1 ==> MS patients
df_ms_idx = filtered_df.index[filtered_df['isms'] == 1].tolist()
#print(df_ms_idx)
print(len(df_ms_idx))
```

```
37
73
```

Group assignments is expected to be [1,1,1,2,2,1,1,...]

In [36]:
```
# 1 = HC
# 2 = MS

assignments = []
for subject in range(len(subject_IDs_group_analysis)):
    if subject in df_control_idx:
        assignments.append(1)
    else:
        assignments.append(2)

assignments = np.array(assignments)
print(assignments)
```

```
[2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 1 1 2 1 1 1 2 1 1 2 2 2 2 2 1 2 2 2 2
2
 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 1 2 2 1 2 2 1 1 1 2 1
1
 1 1 2 1 2 1 2 1 2 1 1 2 1 1 1 1 1 2 2 1 2 2 2 2 2 2 2 2 1 1 2 2 1 2 2 1]
```

Statistical significance testing - max stat permutation with correction for multiple comparisons

In [37]:
```
from osl_dynamics.analysis import statistics

# Test for a difference in any of the summary statistics
# It's important to combine all the summary statistics into one test to make
sum_stats = [fo, mlt, mintv, sw_rate]
sum_stats = np.swapaxes(sum_stats, 0, 1)  # make sure subjects is the first

# Do stats testing
diff, pvalues = statistics.group_diff_max_stat_perm(
```

```
    sum_stats,
    assignments, # uses the group assignments from previous cell
    n_perm=10000,
)

# Are any summary stat differences significant?
print("Number of significant differences:", np.sum(pvalues < 0.05))
```

```
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Differentia
l) with mode=row-shuffle
        Computing 10000 permutations
        Taking max-stat across ['features 1', 'features 2'] dimensions
Using tstats as metric
Number of significant differences: 1
```

In [40]:
```
# 2nd metric (mean lifetime) - State 7
print(pvalues[1][6])
```

```
0.030000000000000027
```

In [58]:
```
print(np.shape(sum_stats))
```

```
(110, 4, 6)
```

In [41]:
```
# Print the mean (across all subjects) of each metric per state

metric_names = ['FO', 'MLT', 'MI', 'SR']


for metric in range(len(metric_names)):
    data_metric = sum_stats[:, metric]
    for state in range(n_states):
        data_state = data_metric[:,state]
        print(metric_names[metric], '-', 'state', state+1, ':', np.round(np..
                  '+/-', np.round(np.std(data_state),2))
```

```
FO - state 1 : 0.19 +/- 0.07
FO - state 2 : 0.16 +/- 0.08
FO - state 3 : 0.16 +/- 0.04
FO - state 4 : 0.17 +/- 0.03
FO - state 5 : 0.06 +/- 0.04
FO - state 6 : 0.08 +/- 0.03
FO - state 7 : 0.02 +/- 0.01
FO - state 8 : 0.16 +/- 0.04
MLT - state 1 : 65.03 +/- 9.46
MLT - state 2 : 82.69 +/- 32.37
MLT - state 3 : 72.87 +/- 12.23
MLT - state 4 : 65.09 +/- 9.07
MLT - state 5 : 3177.9 +/- 961.72
MLT - state 6 : 75.92 +/- 18.35
MLT - state 7 : 54.79 +/- 17.5
MLT - state 8 : 63.37 +/- 8.05
MI - state 1 : 309.44 +/- 129.26
MI - state 2 : 493.53 +/- 207.0
MI - state 3 : 376.97 +/- 83.29
MI - state 4 : 330.83 +/- 73.93
MI - state 5 : 79165.07 +/- 67713.96
MI - state 6 : 984.97 +/- 289.55
MI - state 7 : 2533.48 +/- 1039.5
MI - state 8 : 332.71 +/- 77.1
SR - state 1 : 2.86 +/- 0.74
SR - state 2 : 1.84 +/- 0.42
SR - state 3 : 2.26 +/- 0.37
SR - state 4 : 2.57 +/- 0.45
SR - state 5 : 0.02 +/- 0.01
SR - state 6 : 0.98 +/- 0.23
SR - state 7 : 0.43 +/- 0.15
SR - state 8 : 2.57 +/- 0.4
```

In [42]:

```python
# Print the group means and standard deviation for each summary metric, per
sum_stats[df_control_idx][:][0][0]    # 1st for metric, 2nd for state number

groups = [df_control_idx, df_ms_idx]
group_names = ['HC', 'PwMS']
metric_names = ['FO', 'MLT', 'MI', 'SR']
for group in range(len(groups)):
    group_stats = sum_stats[groups[group]]
    for metric in range(len(metric_names)):
        group_metric = group_stats[:, metric]
        for state in range(n_states):
            group_state = group_metric[:,state]
            print(group_names[group], '-', metric_names[metric], '-', 'state
                  '+/-', np.round(np.std(group_state),2))
```

```
HC - FO - state 1 : 0.2 +/- 0.06
HC - FO - state 2 : 0.15 +/- 0.07
HC - FO - state 3 : 0.17 +/- 0.03
HC - FO - state 4 : 0.16 +/- 0.04
HC - FO - state 5 : 0.06 +/- 0.04
HC - FO - state 6 : 0.07 +/- 0.02
HC - FO - state 7 : 0.02 +/- 0.01
HC - FO - state 8 : 0.17 +/- 0.04
HC - MLT - state 1 : 66.79 +/- 9.19
HC - MLT - state 2 : 80.25 +/- 31.47
HC - MLT - state 3 : 72.67 +/- 11.8
HC - MLT - state 4 : 65.88 +/- 9.2
HC - MLT - state 5 : 3152.14 +/- 1052.84
HC - MLT - state 6 : 76.7 +/- 17.26
HC - MLT - state 7 : 47.47 +/- 12.17
HC - MLT - state 8 : 63.72 +/- 8.45
HC - MI - state 1 : 288.81 +/- 103.23
HC - MI - state 2 : 486.87 +/- 183.87
HC - MI - state 3 : 361.32 +/- 64.73
HC - MI - state 4 : 348.67 +/- 92.38
HC - MI - state 5 : 75620.36 +/- 77203.04
HC - MI - state 6 : 988.7 +/- 266.61
HC - MI - state 7 : 2645.1 +/- 1115.29
HC - MI - state 8 : 326.37 +/- 78.14
HC - SR - state 1 : 2.95 +/- 0.66
HC - SR - state 2 : 1.85 +/- 0.39
HC - SR - state 3 : 2.32 +/- 0.31
HC - SR - state 4 : 2.47 +/- 0.47
HC - SR - state 5 : 0.02 +/- 0.01
HC - SR - state 6 : 0.96 +/- 0.2
HC - SR - state 7 : 0.41 +/- 0.15
HC - SR - state 8 : 2.6 +/- 0.4
PwMS - FO - state 1 : 0.19 +/- 0.07
PwMS - FO - state 2 : 0.16 +/- 0.08
PwMS - FO - state 3 : 0.16 +/- 0.04
PwMS - FO - state 4 : 0.17 +/- 0.03
PwMS - FO - state 5 : 0.06 +/- 0.04
PwMS - FO - state 6 : 0.08 +/- 0.03
PwMS - FO - state 7 : 0.03 +/- 0.01
PwMS - FO - state 8 : 0.16 +/- 0.04
PwMS - MLT - state 1 : 64.14 +/- 9.47
PwMS - MLT - state 2 : 83.92 +/- 32.75
PwMS - MLT - state 3 : 72.98 +/- 12.45
PwMS - MLT - state 4 : 64.69 +/- 8.97
PwMS - MLT - state 5 : 3190.96 +/- 911.8
PwMS - MLT - state 6 : 75.53 +/- 18.87
PwMS - MLT - state 7 : 58.5 +/- 18.59
PwMS - MLT - state 8 : 63.2 +/- 7.83
PwMS - MI - state 1 : 319.9 +/- 139.47
PwMS - MI - state 2 : 496.91 +/- 217.71
PwMS - MI - state 3 : 384.91 +/- 90.24
PwMS - MI - state 4 : 321.79 +/- 60.55
PwMS - MI - state 5 : 80961.71 +/- 62278.41
PwMS - MI - state 6 : 983.07 +/- 300.49
PwMS - MI - state 7 : 2476.9 +/- 994.11
PwMS - MI - state 8 : 335.92 +/- 76.37
PwMS - SR - state 1 : 2.82 +/- 0.77
PwMS - SR - state 2 : 1.84 +/- 0.44
PwMS - SR - state 3 : 2.23 +/- 0.39
PwMS - SR - state 4 : 2.62 +/- 0.44
PwMS - SR - state 5 : 0.02 +/- 0.01
PwMS - SR - state 6 : 0.99 +/- 0.24
PwMS - SR - state 7 : 0.44 +/- 0.15
PwMS - SR - state 8 : 2.55 +/- 0.4
```

2. Temporal characteristics - Evoked response Analysis

```
- Extracted filtered epochs (no bad_segments epochs & only
128 first trials)
- Seperate correct vs. incorrect trials (1st level)
- Epoch the state's timecourse + baseline correct
- significance testing (max statistic permutation testing)
between the states at each timepoint
- HC vs. MS for each state seperately (2nd level)
```

Extract timestamps for correct & incorrect trials

For **all epochs**

In [43]:
```
def get_raw_stimuli(all_parceled_paths, nr_subject: int, df_events_all):

    ## Extract event timestamps
    ########################################

    raw = mne.io.read_raw_fif(all_parceled_paths[nr_subject])
    start_time_sample = raw.first_samp

    df_events = df_events_all[nr_subject]
    list_correct = df_events.loc[df_events['trial_type'] == 'trial_correct']
    list_incorrect = df_events.loc[df_events['trial_type'] == 'trial_incorre

    # Only keep the 38 parcels, no STIM channels
    ch_names_python = []
    for i in range(38):
        ch_names_python.append('parcel_' + str(i))
    raw = raw.pick(ch_names_python)

    ## keep all trials
    #######################################

    #merged_list = sorted(np.concatenate((list_correct,list_incorrect)))

    # keep all trials
    #if len(merged_list) > 128:
        #result_elements = merged_list[:128]

        # Remove the elements from list_correct and list_incorrect that do r
        #list_correct = [element for element in list_correct if element in i
        #list_incorrect = [element for element in list_incorrect if element

    # Extract events -> correction for unwanted time-shift applied here wher
    events_correct = [raw.time_as_index(timestamp)[0] for timestamp in list_
    events_incorrect = [raw.time_as_index(timestamp)[0] for timestamp in lis

    return [np.array(events_correct), np.array(events_incorrect)]
```

For **filtered epochs:**

```
- do not use "bad segments" epochs
- same amount of epochs across all subjects (= 128)
```

In [44]:
```
def extract_filtered_epochs(all_data_files, all_epochs_files, nr_subject):

    # Load .fif file (needed for extracting start_time_sample)
    raw = mne.io.read_raw_fif(all_data_files[nr_subject])
    start_time_sample = raw.first_samp

    # Load previously saved events (correctly saved)
    loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=Tr
    events = loaded_epochs.events

    # Correct for the timeshift
    sample_indices = events[:,0] - start_time_sample

    # Add trials to correct OR incorrect list
    event_type = events[:,2]
    events_correct = []
    events_incorrect = []
    for idx in range(len(event_type)):
        if event_type[idx] == 1:         # correct trial
            events_correct.append(sample_indices[idx])
        else:
            events_incorrect.append(sample_indices[idx])

    return [np.array(events_correct), np.array(events_incorrect)]
```

In [45]:
```
all_epochs_paths = sorted(glob.glob('/home/olivierb/FULLY_PROCESSED/Epoched_
#print(len(all_epochs_paths))
event_indices_filtered = []

subs = len(subject_IDs_group_analysis)
for i in range(subs):
    event_indices_filtered.append(extract_filtered_epochs(input_data_HMM, al

# Correct & incorrect trials per subject are both in this array
event_indices_filtered_all = [np.concatenate(subject_epochs) for subject_epo
```

```
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_0925_raw.f
if...
    Range : 26250 ... 325749 =    105.000 ...  1302.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_0925_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
128 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_0944_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 32500 ... 330749 =    130.000 ...  1322.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_0944_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
127 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_0945_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 33000 ... 343999 =    132.000 ...  1375.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_0945_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
110 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_0947_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 22250 ... 353499 =     89.000 ...  1413.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_0947_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
126 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_0987_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 18250 ... 279249 =     73.000 ...  1116.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_0987_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
126 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_0992_raw.fi
f...
    Range : 38750 ... 321749 =    155.000 ...  1286.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_0992_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
120 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_0995_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 22000 ... 296499 =     88.000 ...  1185.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_0995_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
110 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_0997_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 10500 ... 283499 =     42.000 ...  1133.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_0997_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
125 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_0999_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 4250 ... 268999 =     17.000 ...  1075.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_0999_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
128 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1000_raw.fi
f...
    Range : 10750 ... 273999 =     43.000 ...  1095.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1000_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
126 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1001_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 25000 ... 281999 =    100.000 ...  1127.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1001_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
118 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1002_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 59250 ... 386749 =    237.000 ...  1546.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1002_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
127 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1005_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 15750 ... 288749 =     63.000 ...  1154.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1005_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
114 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1006_raw.f
if...
    Range : 43500 ... 314249 =    174.000 ...  1256.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1006_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
Not setting metadata
120 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1007_raw.fi
f...
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
    Range : 39750 ... 319499 =    159.000 ...  1277.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1007_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
125 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1008_raw.f
if...
    Range : 34250 ... 280749 =    137.000 ...  1122.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1008_sub
-epo.fif ...
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
125 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1009_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 4000 ... 280499 =     16.000 ...  1121.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1009_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
117 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1010_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 31500 ... 270499 =    126.000 ...  1081.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1010_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
117 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1017_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 32500 ... 327499 =    130.000 ...  1309.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1017_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
128 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1018_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 36500 ... 318249 =    146.000 ...  1272.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1018_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
124 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1023_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 32750 ... 290749 =    131.000 ...  1162.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1023_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
124 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1024_raw.f
if...
    Range : 42000 ... 327999 =    168.000 ...  1311.996 secs
Ready.
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1024_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
124 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1025_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 25750 ... 264749 =    103.000 ...  1058.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1025_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
104 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1028_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 34000 ... 337999 =    136.000 ...  1351.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1028_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
126 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1031_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 25500 ... 283999 =    102.000 ...  1135.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1031_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
125 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1033_raw.fi
f...
    Range : 12000 ... 216999 =     48.000 ...   867.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1033_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
126 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1052_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 42250 ... 314499 =    169.000 ...  1257.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1052_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
125 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1053_raw.fi
f...
    Range : 12750 ... 252749 =     51.000 ...  1010.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1053_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
125 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1073_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 29500 ... 302249 =    118.000 ...  1208.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1073_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
127 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1078_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 29250 ... 281249 =    117.000 ...  1124.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1078_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
121 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1082_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 14750 ... 283999 =     59.000 ...  1135.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1082_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
117 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1097_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 17750 ... 293749 =     71.000 ...  1174.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1097_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
125 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_1106_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 36250 ... 342749 =    145.000 ...  1370.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_1106_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
125 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2096_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 4500 ... 134249 =     18.000 ...   536.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2096_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
116 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2102_raw.f
if...
    Range : 5500 ... 163249 =     22.000 ...   652.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2102_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
Not setting metadata
108 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2121_raw.fi
f...
    Range : 8000 ... 173249 =     32.000 ...   692.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2121_sub-e
po.fif ...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
126 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2122_raw.f
if...
    Range : 6250 ... 179499 =     25.000 ...   717.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2122_sub
-epo.fif ...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
125 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2144_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 12000 ... 141999 =     48.000 ...   567.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2144_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
120 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2147_raw.fi
f...
    Range : 5500 ... 149999 =     22.000 ...   599.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2147_sub-e
po.fif ...
    Found the data of interest:
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
119 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2150_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 4750 ... 143999 =     19.000 ...   575.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2150_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
115 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2151_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 7250 ... 149249 =     29.000 ...   596.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2151_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
123 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2163_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 9250 ... 141499 =     37.000 ...   565.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2163_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
103 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2164_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 4000 ... 160499 =     16.000 ...   641.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2164_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
124 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2169_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 32750 ... 189249 =    131.000 ...   756.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2169_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
124 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2172_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 9000 ... 138999 =     36.000 ...   555.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2172_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
115 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2173_raw.f
if...
    Range : 13500 ... 163999 =     54.000 ...   655.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2173_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
120 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2179_raw.fi
f...
    Range : 6250 ... 143749 =     25.000 ...   574.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2179_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
115 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2189_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 4000 ... 132749 =     16.000 ...   530.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2189_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
122 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2190_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 7500 ... 147499 =     30.000 ...   589.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2190_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
99 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2192_raw.fi
f...
    Range : 6500 ... 168999 =     26.000 ...   675.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2192_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
122 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2193_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 9000 ... 163999 =     36.000 ...   655.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2193_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
105 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2201_raw.fi
f...
    Range : 4000 ... 138749 =     16.000 ...   554.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2201_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
118 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2203_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 19750 ... 152249 =     79.000 ...   608.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2203_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
123 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2206_raw.f
if...
    Range : 2500 ... 127749 =     10.000 ...   510.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2206_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
Not setting metadata
126 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2211_raw.f
if...
    Range : 8750 ... 179999 =     35.000 ...   719.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2211_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
122 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2215_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 11750 ... 154749 =     47.000 ...   618.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2215_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
123 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2220_raw.fi
f...
    Range : 13250 ... 137749 =     53.000 ...   550.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2220_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
111 matching events found
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2221_raw.f
if...
    Range : 5500 ... 146749 =     22.000 ...   586.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2221_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
121 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2224_raw.f
if...
    Range : 3250 ... 138249 =     13.000 ...   552.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2224_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
Not setting metadata
118 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2226_raw.f
if...
    Range : 3500 ... 153249 =     14.000 ...   612.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2226_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
125 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2227_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 3000 ... 132999 =     12.000 ...   531.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2227_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
123 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2235_raw.fi
f...
    Range : 6500 ... 146999 =     26.000 ...   587.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2235_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
113 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2238_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 5500 ... 137499 =     22.000 ...   549.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2238_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
103 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2239_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 5750 ... 144999 =     23.000 ...   579.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2239_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
123 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2241_raw.fi
f...
    Range : 5500 ... 141999 =     22.000 ...   567.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2241_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
106 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2252_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 4250 ... 137749 =     17.000 ...   550.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2252_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
115 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2257_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 6750 ... 140749 =     27.000 ...   562.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2257_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
122 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2264_raw.f
if...
    Range : 5500 ... 132499 =     22.000 ...   529.996 secs
Ready.
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2264_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
115 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2266_raw.f
if...
    Range : 4750 ... 130999 =     19.000 ...   523.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2266_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
123 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2267_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 4500 ... 128999 =     18.000 ...   515.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2267_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
112 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2268_raw.fi
f...
    Range : 5750 ... 134249 =     23.000 ...   536.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2268_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
121 matching events found
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2277_raw.f
if...
    Range : 3500 ... 140499 =     14.000 ...   561.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2277_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
110 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2278_raw.f
if...
    Range : 4500 ... 146999 =     18.000 ...   587.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2278_sub
-epo.fif ...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
119 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2279_raw.f
if...
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
    Range : 8750 ... 129749 =     35.000 ...   518.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2279_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
110 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2292_raw.fi
f...
    Range : 6750 ... 150249 =     27.000 ...   600.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2292_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
124 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2300_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 4000 ... 137249 =     16.000 ...   548.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2300_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
120 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2305_raw.f
if...
    Range : 4500 ... 148499 =     18.000 ...   593.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2305_sub
-epo.fif ...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
110 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2306_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 9000 ... 139499 =     36.000 ...   557.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2306_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
127 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2311_raw.f
if...
    Range : 2250 ... 129499 =      9.000 ...   517.996 secs
Ready.
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2311_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
125 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2312_raw.fi
f...
    Range : 2750 ... 136749 =     11.000 ...   546.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2312_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
Not setting metadata
121 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2313_raw.f
if...
    Range : 4500 ... 169249 =     18.000 ...   676.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2313_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
124 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2314_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 12250 ... 130999 =     49.000 ...   523.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2314_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
127 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2317_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 8750 ... 132999 =     35.000 ...   531.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2317_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
119 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2318_raw.fi
f...
    Range : 6000 ... 116499 =     24.000 ...   465.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2318_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
121 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2319_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 8000 ... 138249 =     32.000 ...   552.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2319_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
120 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2324_raw.fi
f...
    Range : 5500 ... 156749 =     22.000 ...   626.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2324_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
116 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2325_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 6500 ... 136249 =     26.000 ...   544.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2325_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
122 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2327_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 2750 ... 129499 =     11.000 ...   517.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2327_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
123 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2328_raw.fi
f...
    Range : 2500 ... 131499 =     10.000 ...   525.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2328_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
123 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2341_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 3250 ... 129499 =     13.000 ...   517.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2341_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
126 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2342_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 5000 ... 123749 =     20.000 ...   494.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2342_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
125 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2343_raw.fi
f...
    Range : 3000 ... 127999 =     12.000 ...   511.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2343_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
124 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2346_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 10000 ... 156999 =     40.000 ...   627.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2346_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
126 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2359_raw.fi
f...
    Range : 4750 ... 149999 =     19.000 ...   599.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2359_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
124 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2363_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 5500 ... 137999 =     22.000 ...   551.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2363_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
117 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2364_raw.fi
f...
    Range : 3750 ... 135749 =     15.000 ...   542.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2364_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
112 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2378_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 4500 ... 142749 =     18.000 ...   570.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2378_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
124 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2379_raw.fi
f...
    Range : 3000 ... 162499 =     12.000 ...   649.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2379_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
105 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2384_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 21750 ... 159999 =     87.000 ...   639.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2384_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
121 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2386_raw.fi
f...
    Range : 6000 ... 156499 =     24.000 ...   625.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2386_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
116 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2388_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 2250 ... 145249 =      9.000 ...   580.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2388_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
124 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2396_raw.f
if...
    Range : 12250 ... 146999 =     49.000 ...   587.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2396_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
Not setting metadata
127 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2410_raw.fi
f...
    Range : 2750 ... 136749 =     11.000 ...   546.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2410_sub-e
po.fif ...
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
128 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2414_raw.fi
f...
    Range : 5000 ... 148999 =     20.000 ...   595.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2414_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
119 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2416_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 8000 ... 177999 =     32.000 ...   711.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2416_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
106 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2421_raw.fi
f...
    Range : 180500 ... 307749 =    722.000 ...  1230.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2421_sub-e
po.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
119 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2427_raw.fi
f...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 3250 ... 127999 =     13.000 ...   511.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2427_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
114 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2440_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 4500 ... 136999 =     18.000 ...   547.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2440_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
117 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2447_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 12750 ... 158249 =     51.000 ...   632.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2447_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
122 matching events found
No baseline correction applied
0 projection items activated
Opening raw data file /home/olivierb/Input_files_HMM/final/sub_2448_raw.f
if...
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

```
    Range : 3500 ... 130249 =     14.000 ...   520.996 secs
Ready.
Reading /home/olivierb/FULLY_PROCESSED/Epoched_data/DIODE/epochs_2448_sub
-epo.fif ...
    Found the data of interest:
        t =    -500.00 ...    1000.00 ms
        0 CTF compensation matrices available
Not setting metadata
124 matching events found
No baseline correction applied
0 projection items activated
```

```
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
/tmp/ipykernel_2243037/47478276.py:8: RuntimeWarning: The events passed t
o the Epochs constructor are not chronologically ordered.
  loaded_epochs = mne.read_epochs(all_epochs_files[nr_subject], preload=T
rue)
```

In [46]:

```
print(np.shape(event_indices_filtered))
#print(event_indices_filtered_all)
```

```
(110, 2)
```

```
/home/olivierb/.local/lib/python3.9/site-packages/numpy/core/fromnumeric.p
y:2009: VisibleDeprecationWarning: Creating an ndarray from ragged nested s
equences (which is a list-or-tuple of lists-or-tuples-or ndarrays with diff
erent lengths or shapes) is deprecated. If you meant to do this, you must s
pecify 'dtype=object' when creating the ndarray.
  result = asarray(a).shape
```

For correct trials

In [64]:

```
# Extract correct & incorrect trials seperately
timings_filtered_correct = [event_indices_filtered[sub][0] for sub in range(
timings_filtered_incorrect = [event_indices_filtered[sub][1] for sub in rang
```

Aligning the state time course to the event timings

In [65]:

```
## 1)
## Pad-locking of alpha (alligning with original MEG timecourse)
# n_embeddings=15 -> 7 (= 15/2 - 1) datapoints are lost from the start and e
timings_filtered_correct_pad = [v - 7 for v in timings_filtered_correct]

## 2)
# Substracting this value might lead to the first event occuring as a negati
# This corresponds to an event we chopped off when we time-delay embedded

# Remove events that we missed due to time-delay embedding
timings_filtered_correct_pad = [v[v > 0] for v in timings_filtered_correct_p

## 3)
# We also lose a few data points from the end of each subject's time series
# -> Let's remove events that we cut off when we separated the training data
timings_filtered_correct_pad = [v[v < s.shape[0]] for v,s in zip(timings_fil
#print(event_indices_tde)
```

Epoching

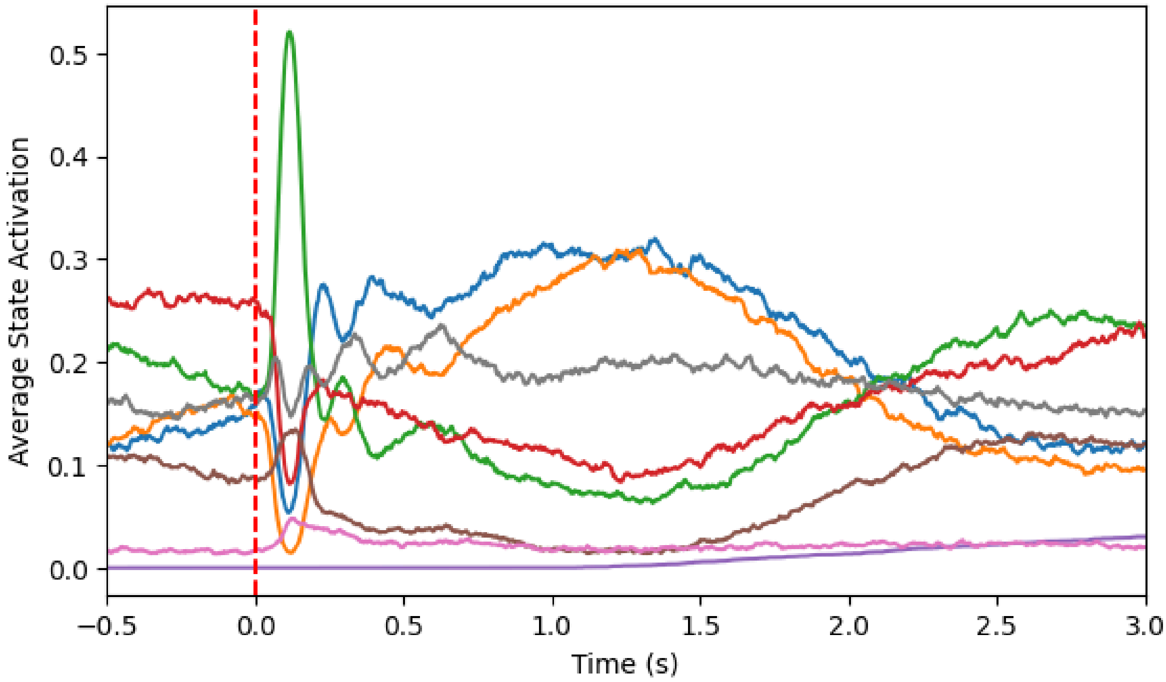
In [66]:
```
# Epoch around events
stc_epochs = []
for s, v in zip(stc, timings_filtered_correct_pad):                    # filte
    stc_epochs.append(task.epoch(s, v, pre=125, post=750))

# Concatenate over subjects
concat_stc_epochs = np.concatenate(stc_epochs)
print(concat_stc_epochs.shape)

# Average over epochs
avg_stc_epoch = np.nanmean(concat_stc_epochs, axis=0)
print(avg_stc_epoch.shape)
```

```
(6287, 875, 8)
(875, 8)
```

Plot

In [67]:
```
fs = 250
n_states = avg_stc_epoch.shape[1]  # number of states
t = (np.arange(avg_stc_epoch.shape[0]) - 250/2) / fs  # time axis

# Plot the visual task
fig, ax = plotting.plot_line(
    [t] * n_states,
    avg_stc_epoch.T,
    x_range=[-0.5, 3],
    x_label="Time (s)",
    y_label="Average State Activation",
)
ax.axvline(color="r", linestyle="--")
```

Out[67]: `<matplotlib.lines.Line2D at 0x7fd129f42d60>`

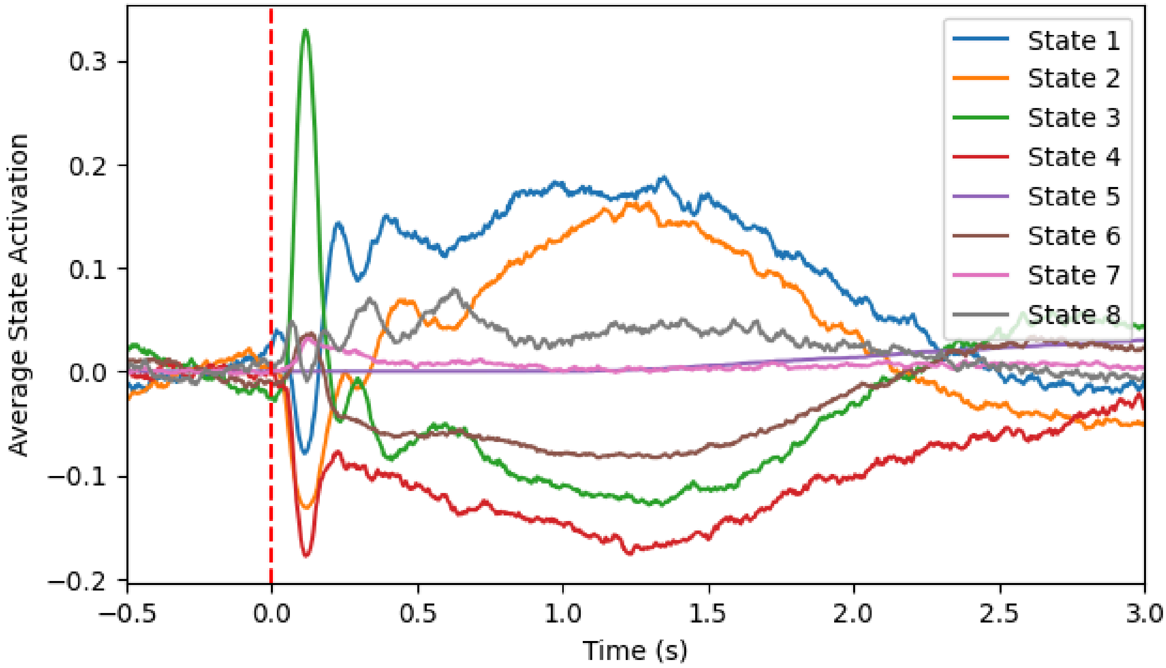


Plot for **baseline corrected**

In [68]:
```
# Calculate the baseline
pre = 125  # number of samples before the event
base_corr = np.nanmean(avg_stc_epoch[:pre], axis=0, keepdims=True)
```

```
# Remove it from the epoched state time courses
corr_avg_stc_epoch = avg_stc_epoch - base_corr

# Plot the visual task
fig, ax = plotting.plot_line(
    [t] * n_states,
    corr_avg_stc_epoch.T,
    labels=[f"State {i}" for i in range(1, n_states + 1)],
    x_range=[-0.5, 3],
    x_label="Time (s)",
    y_label="Average State Activation",
)
ax.axvline(color="r", linestyle="--")
```

Out[68]: <matplotlib.lines.Line2D at 0x7fd1c1b67d60>



Statistical significance testing on evoked responses

In [70]:
```
from osl_dynamics.analysis import statistics

# We already have the trial specific epochs separated by subjects in stc_epo
# we just need to average each subject's trials separately
subj_stc_epochs = []
for epochs in stc_epochs:
    subj_stc_epochs.append(np.nanmean(epochs, axis=0))
subj_stc_epochs = np.array(subj_stc_epochs)
print(subj_stc_epochs.shape)

# Baseline correct using the samples before the event
subj_stc_epochs -= np.mean(subj_stc_epochs[:, :pre], axis=1, keepdims=True)

# Calculate p-values
pvalues = statistics.evoked_response_max_stat_perm(subj_stc_epochs, n_perm=1
print(pvalues.shape)

# Do any time points/states come out as significant?
print("Number of time points with at least 1 state with p-value < 0.05:", np
```

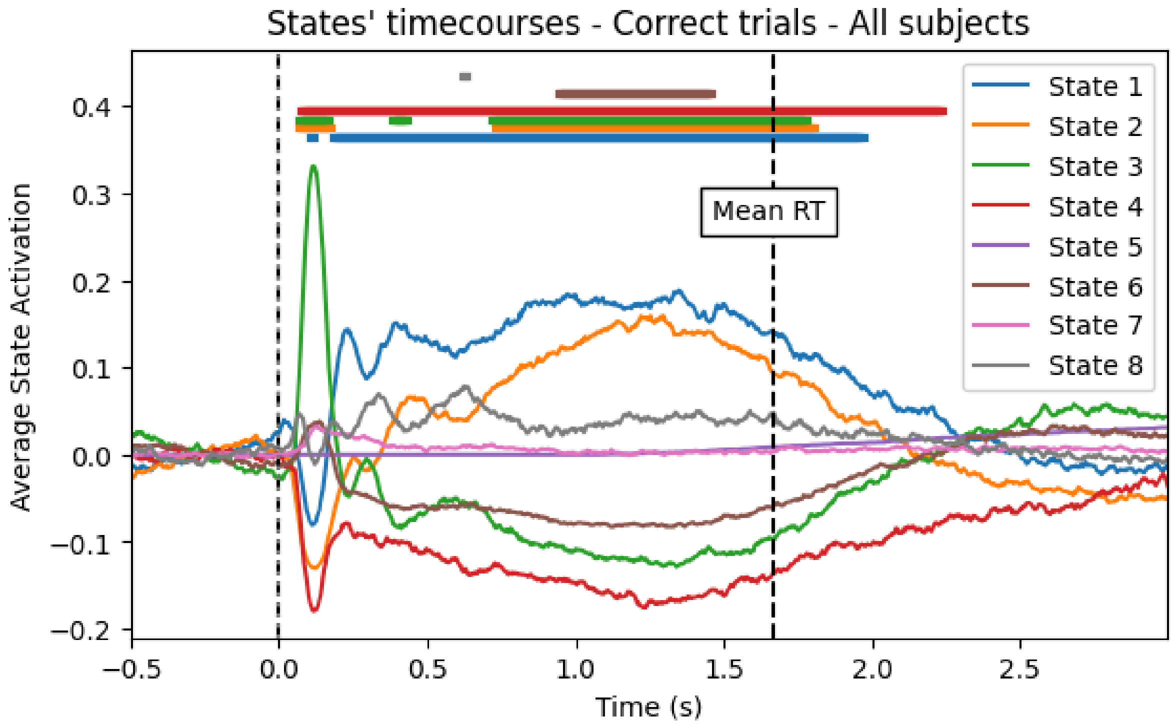
```
(110, 875, 8)
Permuting contrast <class 'glmtools.design.Contrast'>(Mean,MainEffect) wi
th mode=sign-flip
        Computing 1000 permutations
        Taking max-stat across ['time', 'features 1'] dimensions
Using copes as metric
(875, 8)
Number of time points with at least 1 state with p-value < 0.05: 543
```

In [71]:
```
print(np.shape(subj_stc_epochs))
print(np.shape(np.mean(subj_stc_epochs,axis=0)))
```

```
(110, 875, 8)
(875, 8)
```

In [72]:
```
plt.figure()
plotting.plot_evoked_response(
    t,
    np.mean(subj_stc_epochs, axis=0),
    pvalues,
    labels=[f"State {i + 1}" for i in range(subj_stc_epochs.shape[-1])],
    significance_level=0.05,
    x_label="Time (s)",
    y_label="Average State Activation",
    title="States' timecourses - Correct trials - All subjects"
)
plt.axvline(color="gray", linestyle="dotted")
plt.axvline(x=1.668, color="k", linestyle="--")   # 1,668 is the mean reacti
plt.text(1.46, 0.27, 'Mean RT', fontsize = 10, bbox = dict(facecolor = 'whit
```

Out[72]:
```
Text(1.46, 0.27, 'Mean RT')

<Figure size 640x480 with 0 Axes>
```



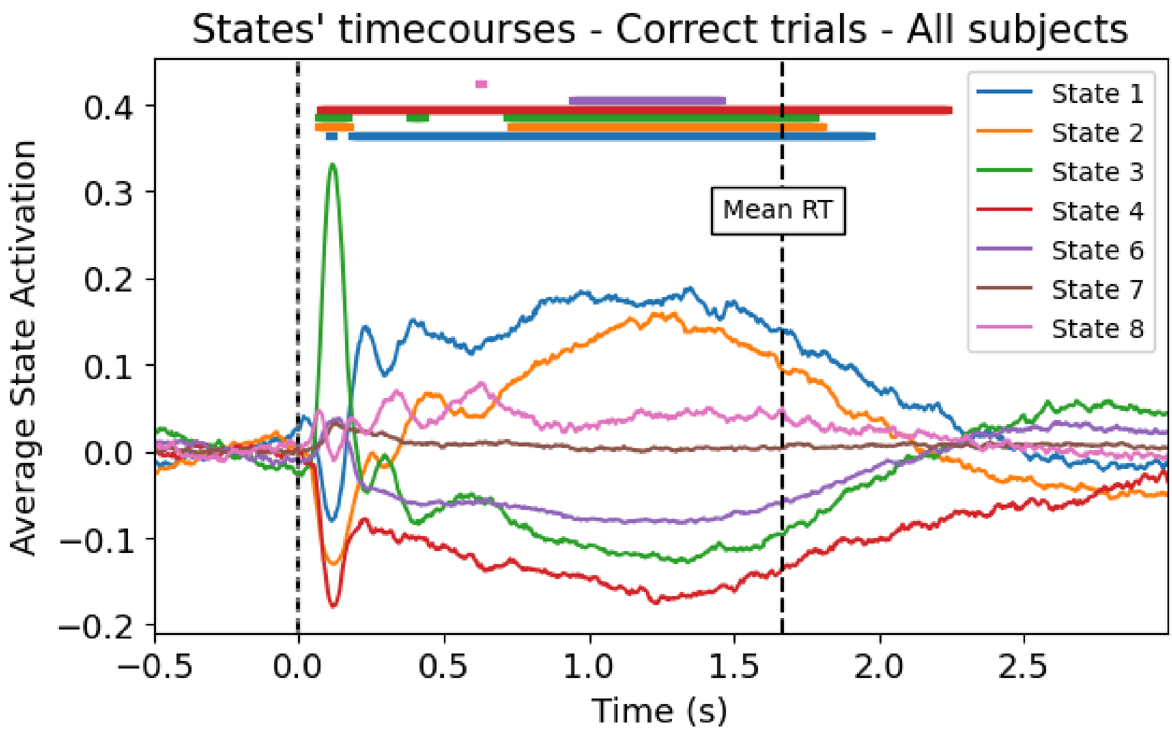
In [73]:
```
subj_stc_epochs_NEW = subj_stc_epochs[:][:,:, np.array([True, True, True, Tr
print(subj_stc_epochs_NEW.shape)

pvalues_NEW = pvalues[:][:, np.array([True, True, True, True, False, True, T

plotting.plot_evoked_response(
    t,
```

```
    np.mean(subj_stc_epochs_NEW, axis=0),
    pvalues_NEW,
    labels=[f"State {i + 1}" for i in [0,1,2,3,5,6,7]],
    significance_level=0.05,
    x_label="Time (s)",
    y_label="Average State Activation",
    title="States' timecourses - Correct trials - All subjects"
)
plt.xlabel("Time (s)", fontsize=13)
plt.ylabel("Average State Activation", fontsize=13)
plt.xticks(fontsize=13)
plt.yticks(fontsize=13)
plt.title("States' timecourses - Correct trials - All subjects", fontsize=15

plt.axvline(color="gray", linestyle="dotted")
plt.axvline(x=1.668, color="k", linestyle="--")   # 1,668 is the mean reacti
plt.text(1.46, 0.27, 'Mean RT', fontsize = 10, bbox = dict(facecolor = 'whit
```

```
(110, 875, 7)
```

Out[73]:

```
Text(1.46, 0.27, 'Mean RT')
```



Same but ZOOMED in

In [56]:

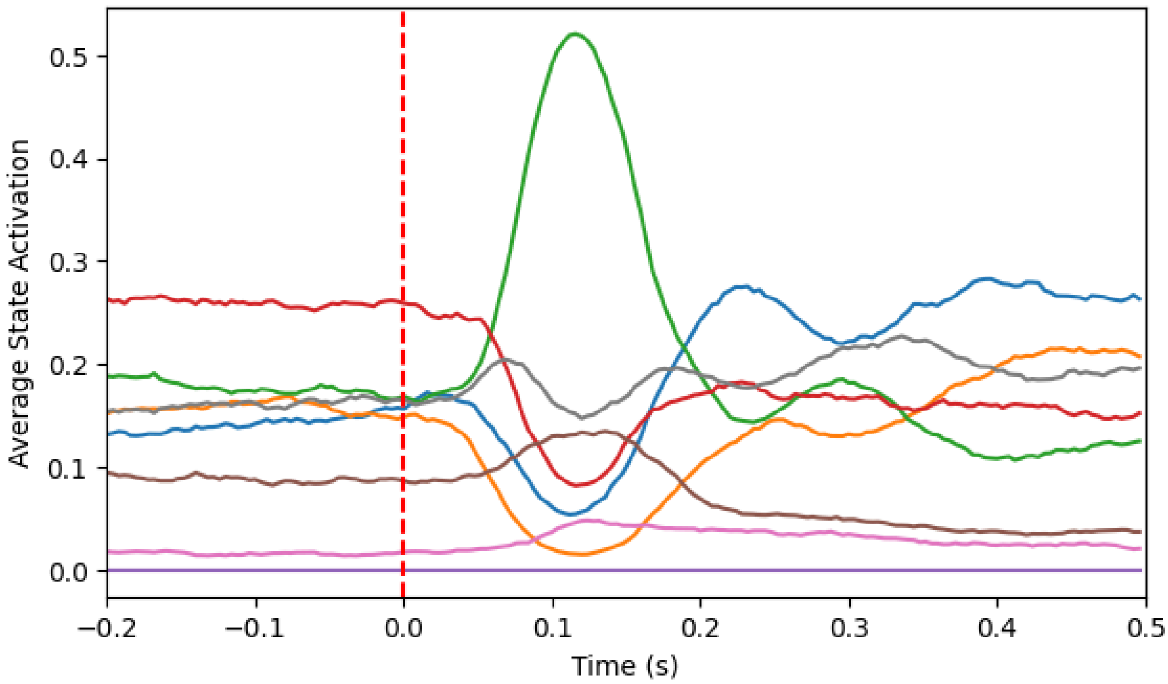
```
# Epoch around events
stc_epochs = []
for s, v in zip(stc, timings_filtered_correct_pad):                # filte
    stc_epochs.append(task.epoch(s, v, pre=50, post=125))

# Concatenate over subjects
concat_stc_epochs = np.concatenate(stc_epochs)
print(concat_stc_epochs.shape)

# Average over epochs
avg_stc_epoch = np.nanmean(concat_stc_epochs, axis=0)
print(avg_stc_epoch.shape)
```

```
(6287, 175, 8)
(175, 8)
```

Plot

In [57]:
```
fs = 250
n_states = avg_stc_epoch.shape[1]  # number of states
t = (np.arange(avg_stc_epoch.shape[0]) - 50) / fs  # time axis

# Plot the visual task
fig, ax = plotting.plot_line(
    [t] * n_states,
    avg_stc_epoch.T,
    x_range=[-0.2, 0.5],
    x_label="Time (s)",
    y_label="Average State Activation",
)
ax.axvline(color="r", linestyle="--")
```

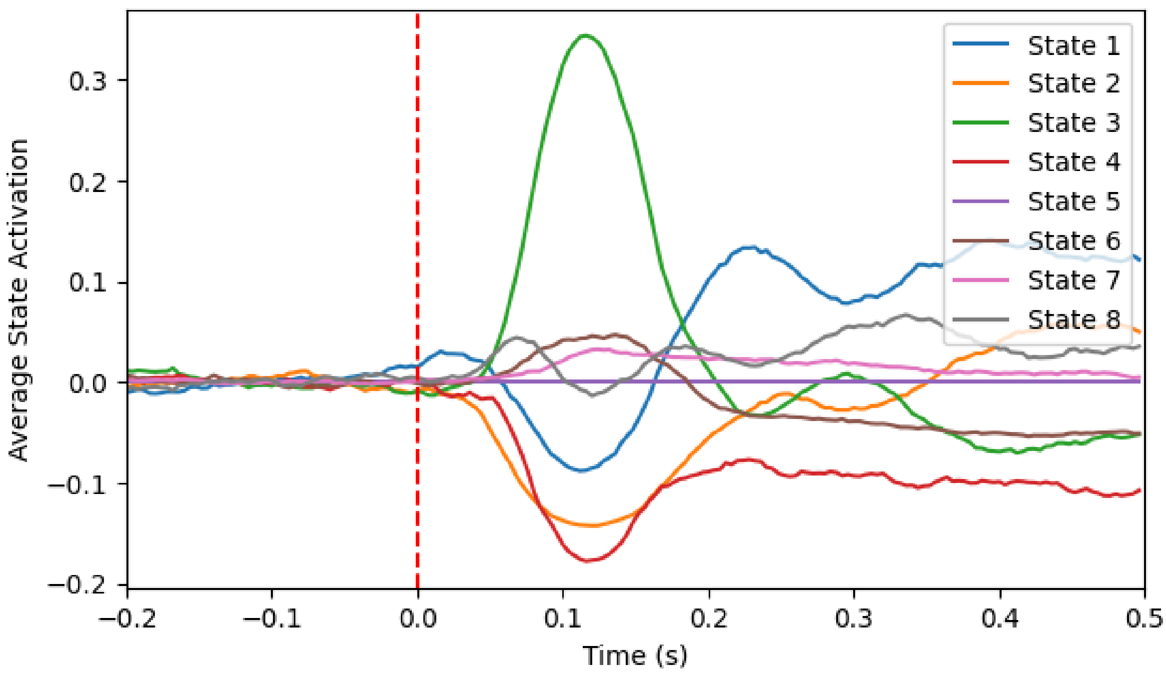
Out[57]: <matplotlib.lines.Line2D at 0x7fd128cb02b0>



Plot for **baseline corrected**

In [58]:
```
# Calculate the baseline
pre = 50  # number of samples before the event
base_corr = np.nanmean(avg_stc_epoch[:pre], axis=0, keepdims=True)

# Remove it from the epoched state time courses
corr_avg_stc_epoch = avg_stc_epoch - base_corr

# Plot the visual task
fig, ax = plotting.plot_line(
    [t] * n_states,
    corr_avg_stc_epoch.T,
    labels=[f"State {i}" for i in range(1, n_states + 1)],
    x_range=[-0.2, 0.5],
    x_label="Time (s)",
    y_label="Average State Activation",
)
ax.axvline(color="r", linestyle="--")
```

Out[58]: <matplotlib.lines.Line2D at 0x7fd1284c3d00>



Statistical significance testing on evoked responses

In [59]:
```
from osl_dynamics.analysis import statistics

# We already have the trial specific epochs separated by subjects in stc_epo
# we just need to average each subject's trials separately
subj_stc_epochs = []
for epochs in stc_epochs:
    subj_stc_epochs.append(np.nanmean(epochs, axis=0))
subj_stc_epochs = np.array(subj_stc_epochs)
print(subj_stc_epochs.shape)

# Baseline correct using the samples before the event
subj_stc_epochs -= np.mean(subj_stc_epochs[:, :pre], axis=1, keepdims=True)

# Calculate p-values
pvalues = statistics.evoked_response_max_stat_perm(subj_stc_epochs, n_perm=1
print(pvalues.shape)

# Do any time points/states come out as significant?
print("Number of time points with at least 1 state with p-value < 0.05:", np
```

```
(110, 175, 8)
Permuting contrast <class 'glmtools.design.Contrast'>(Mean,MainEffect) wi
th mode=sign-flip
        Computing 1000 permutations
        Taking max-stat across ['time', 'features 1'] dimensions
Using copes as metric
(175, 8)
Number of time points with at least 1 state with p-value < 0.05: 109
```

In [60]:
```
print(np.shape(subj_stc_epochs))
print(np.shape(np.mean(subj_stc_epochs,axis=0)))
```

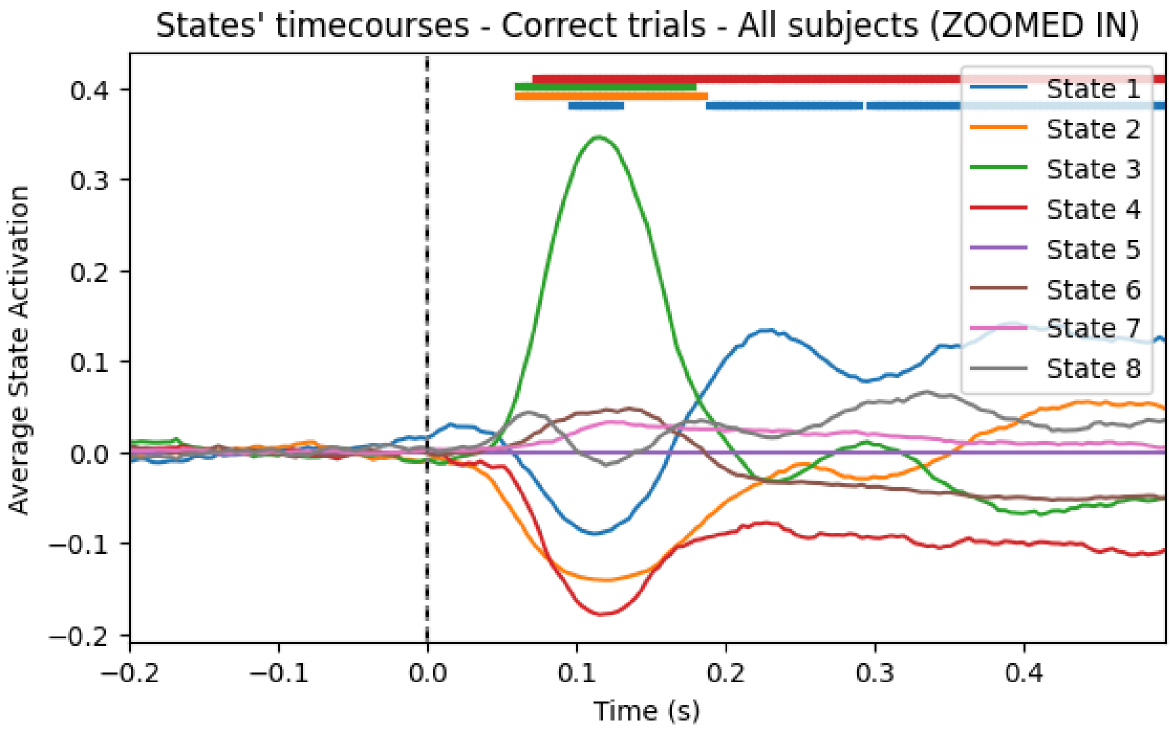
```
(110, 175, 8)
(175, 8)
```

In [61]:
```
plt.figure()
plotting.plot_evoked_response(
```

```
    t,
    np.mean(subj_stc_epochs, axis=0),
    pvalues,
    labels=[f"State {i + 1}" for i in range(subj_stc_epochs.shape[-1])],
    significance_level=0.05,
    x_label="Time (s)",
    y_label="Average State Activation",
    title="States' timecourses - Correct trials - All subjects (ZOOMED IN)"
)
plt.axvline(color="gray", linestyle="dotted")
#plt.axvline(x=1.668, color="k", linestyle="--")   # 1,668 is the mean react
#plt.text(1.46, 0.27, 'Mean RT', fontsize = 10, bbox = dict(facecolor = 'whi
```

Out[61]:
```
<matplotlib.lines.Line2D at 0x7fd128658760>
```

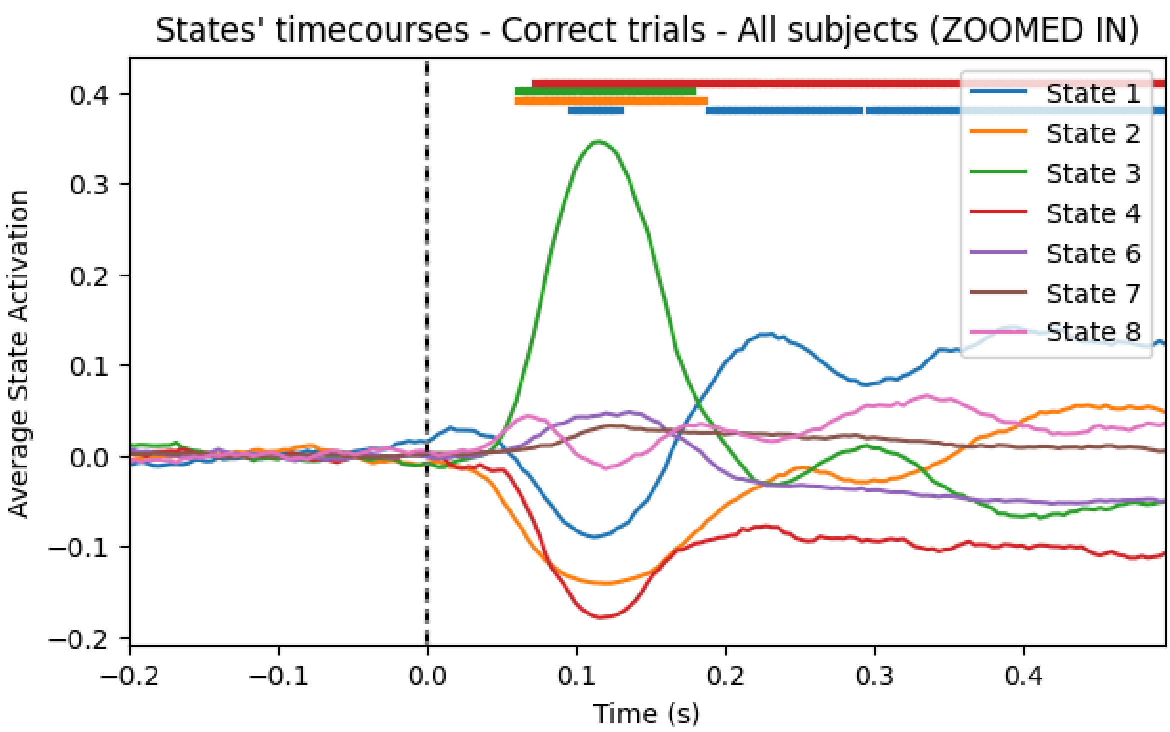
```
<Figure size 640x480 with 0 Axes>
```



In [62]:
```
print(np.shape(subj_stc_epochs))

#labels=['1', '2', '4', '5', '6']
subj_stc_epochs_NEW = subj_stc_epochs[:][:,:, np.array([True, True, True, Tr
print(subj_stc_epochs_NEW.shape)

pvalues_NEW = pvalues[:][:, np.array([True, True, True, True, False, True, T

plotting.plot_evoked_response(
    t,
    np.mean(subj_stc_epochs_NEW, axis=0),
    pvalues_NEW,
    labels=[f"State {i + 1}" for i in [0,1,2,3,5,6,7]],
    significance_level=0.05,
    x_label="Time (s)",
    y_label="Average State Activation",
    title="States' timecourses - Correct trials - All subjects (ZOOMED IN)"
)
plt.axvline(color="gray", linestyle="dotted")
#plt.axvline(x=1.668, color="k", linestyle="--")   # 1,668 is the mean react
#plt.text(1.46, 0.27, 'Mean RT', fontsize = 10, bbox = dict(facecolor = 'whi
```

```
(110, 175, 8)
(110, 175, 7)
```

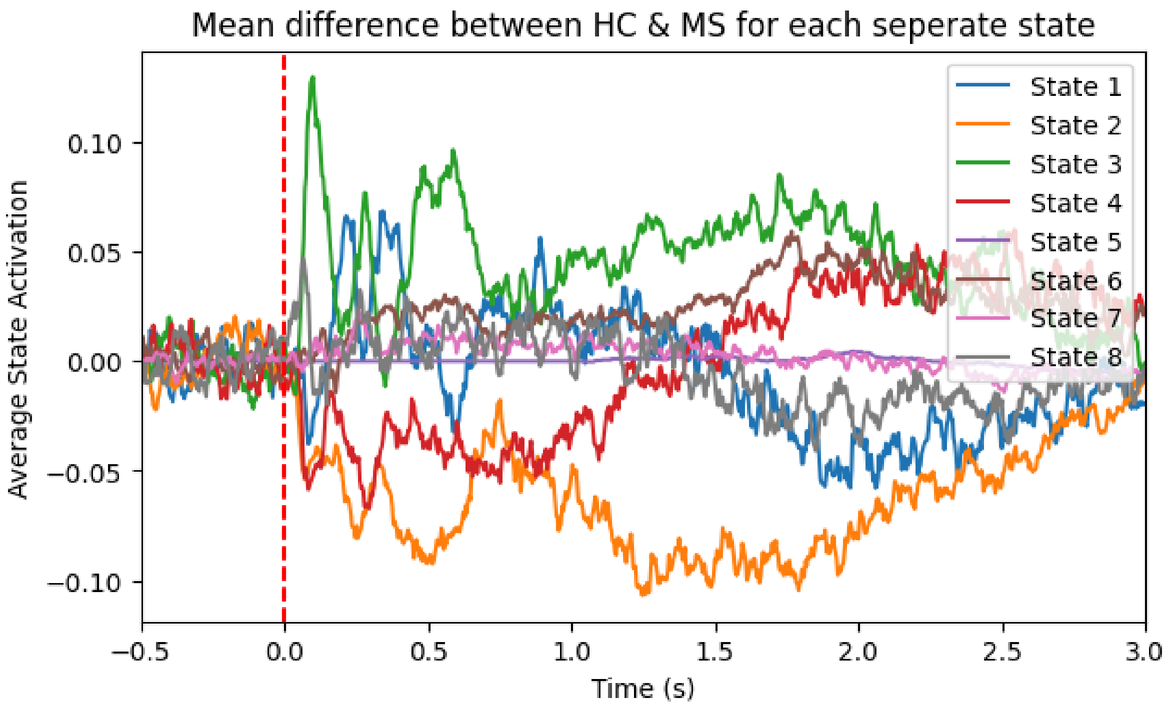
Out[62]: <matplotlib.lines.Line2D at 0x7fd2200ca550>

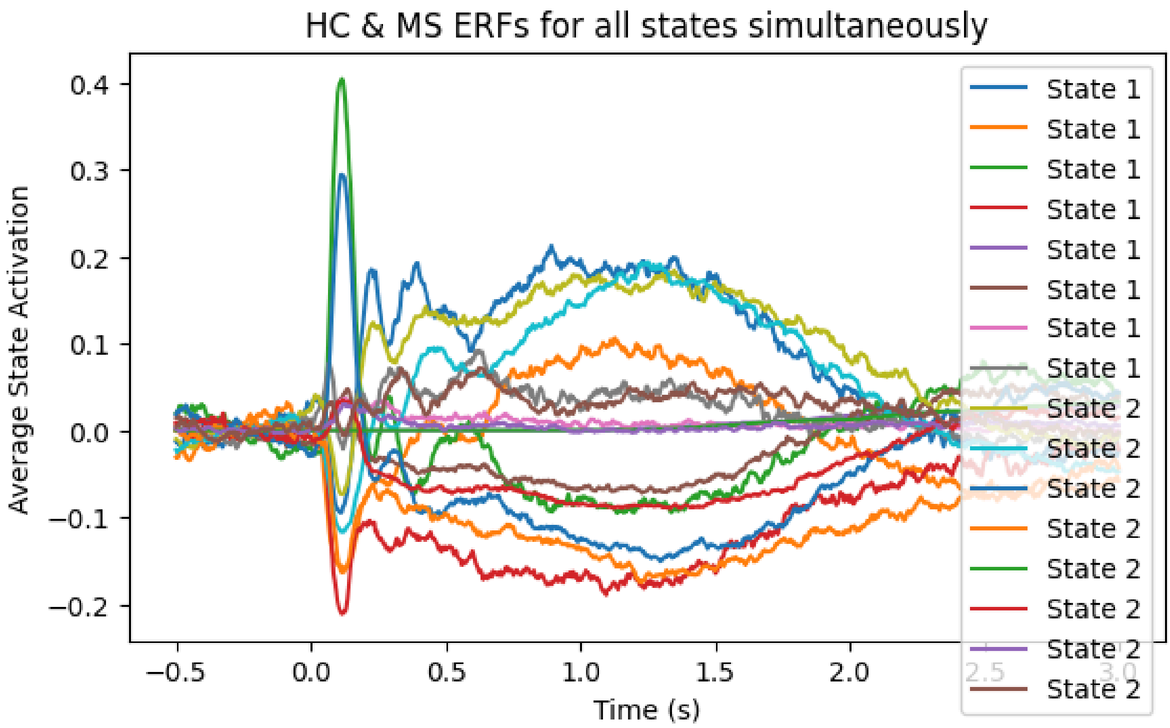


Group comparison (HC vs. MS)

In [74]:
```
# ex. for state 1
epochs_correct_control = [subj_stc_epochs[sub] for sub in range(len(subj_stc
epochs_correct_ms = [subj_stc_epochs[sub] for sub in range(len(subj_stc_epoc

print(np.shape(epochs_correct_control))
print(np.shape(epochs_correct_ms))

group_diff = []
for i in range(n_states):
    group_diff.append(np.mean(epochs_correct_control,axis=0)[:,i] - np.mean(

# Plot the visual task
fig, ax = plotting.plot_line(
    [t] * n_states,
    np.array(group_diff),
    labels=[f"State {i}" for i in range(1, n_states + 1)],
    x_range=[-0.5, 3],
    x_label="Time (s)",
    y_label="Average State Activation",
    title = 'Mean difference between HC & MS for each seperate state'
)
ax.axvline(color="r", linestyle="--")

plotting.plot_line(
    [t,t],
    [np.mean(epochs_correct_control, axis=0),np.mean(epochs_correct_ms, axis
    labels=[f"State {i + 1}" for i in range(2)],
    x_label="Time (s)",
    y_label="Average State Activation",
    title = 'HC & MS ERFs for all states simultaneously'
)

print(np.shape(np.mean(epochs_correct_control,axis=0)))
```

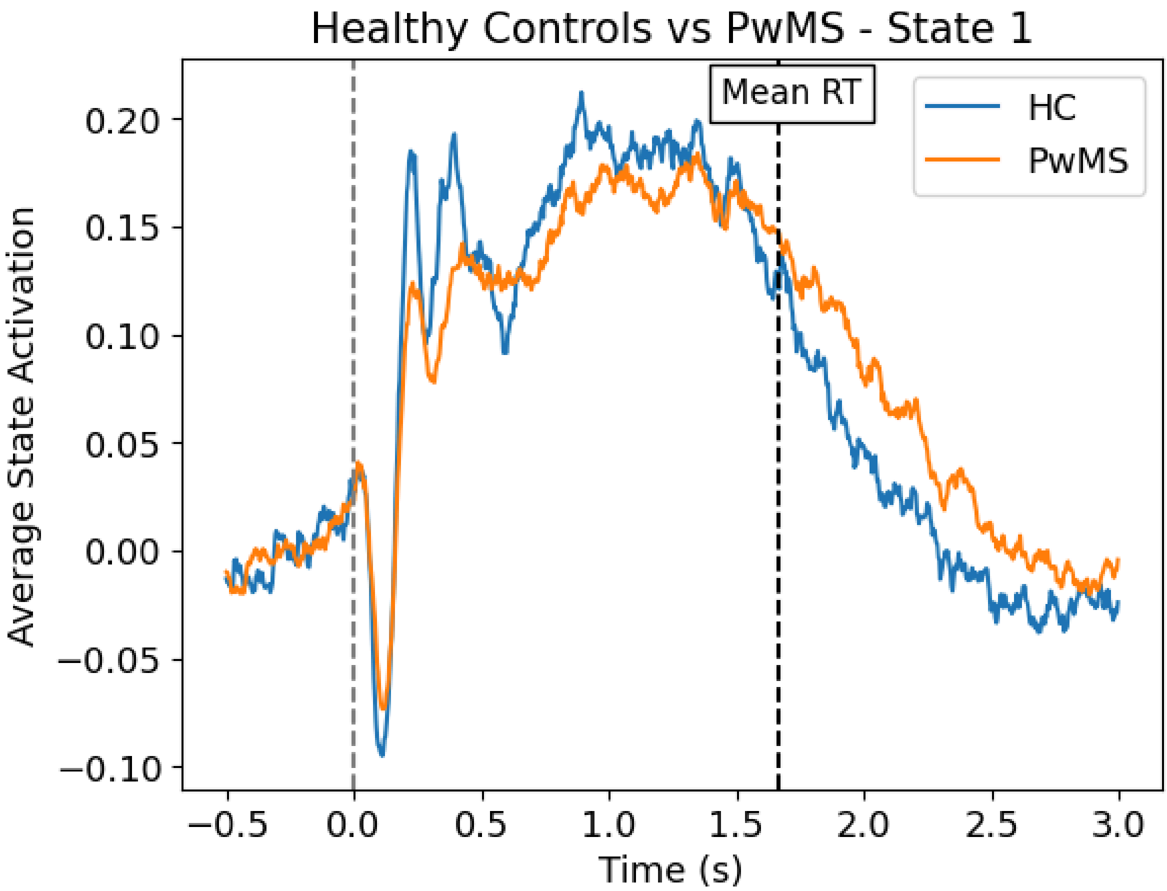
```
(37, 875, 8)
(73, 875, 8)
(875, 8)
```

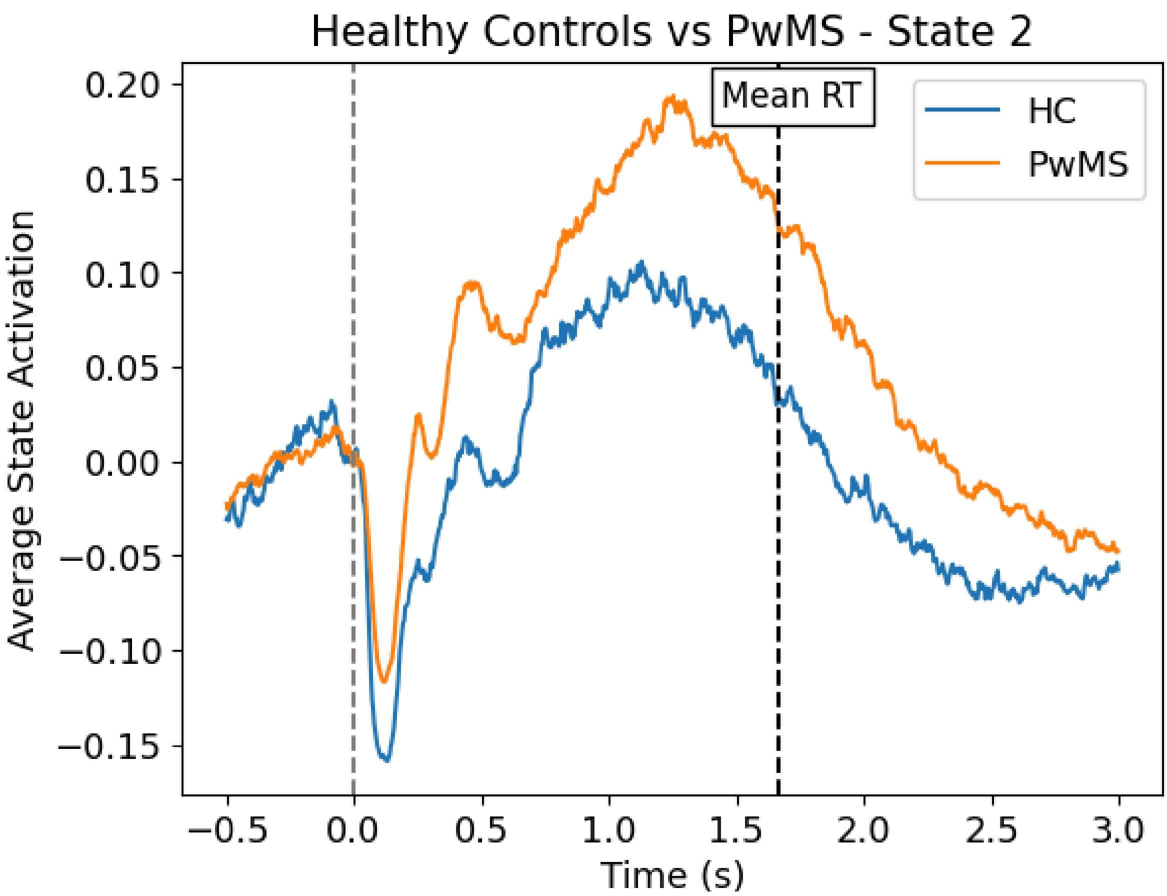


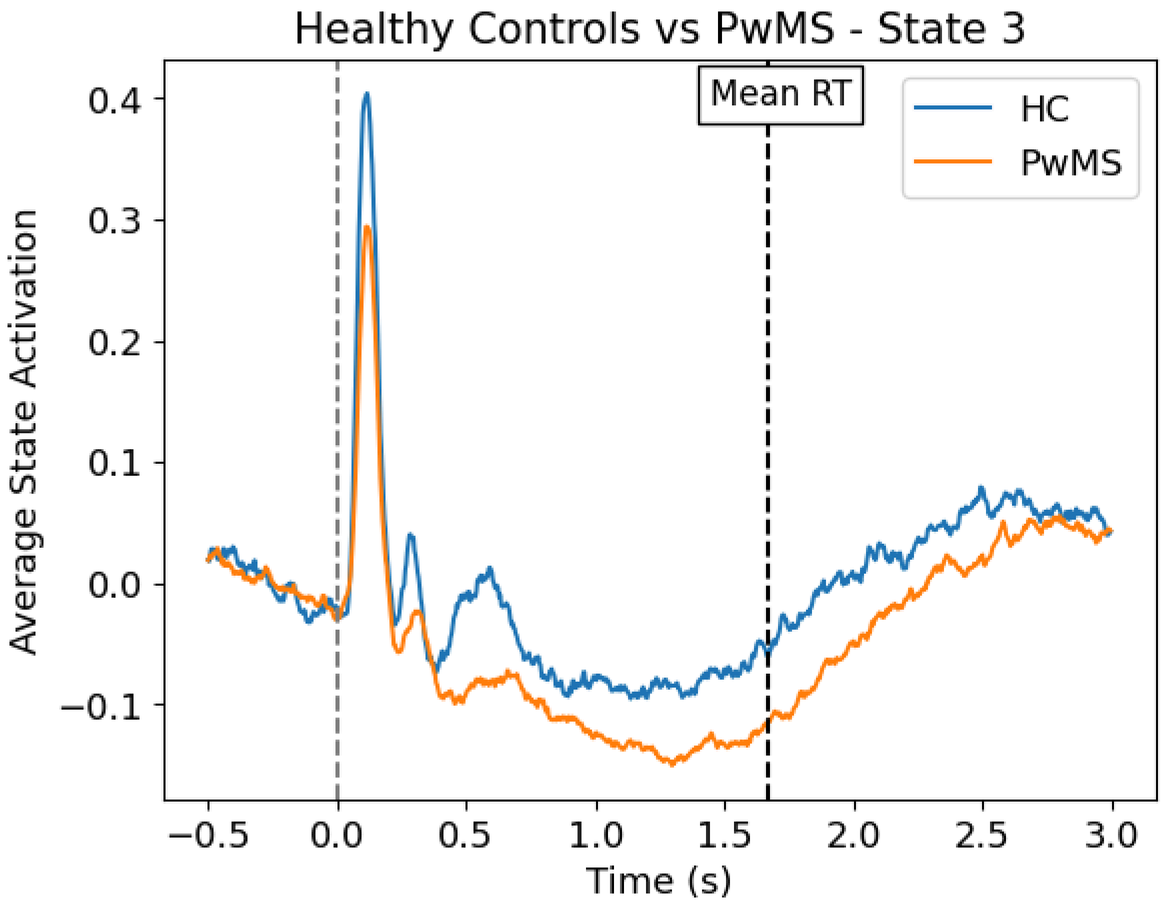


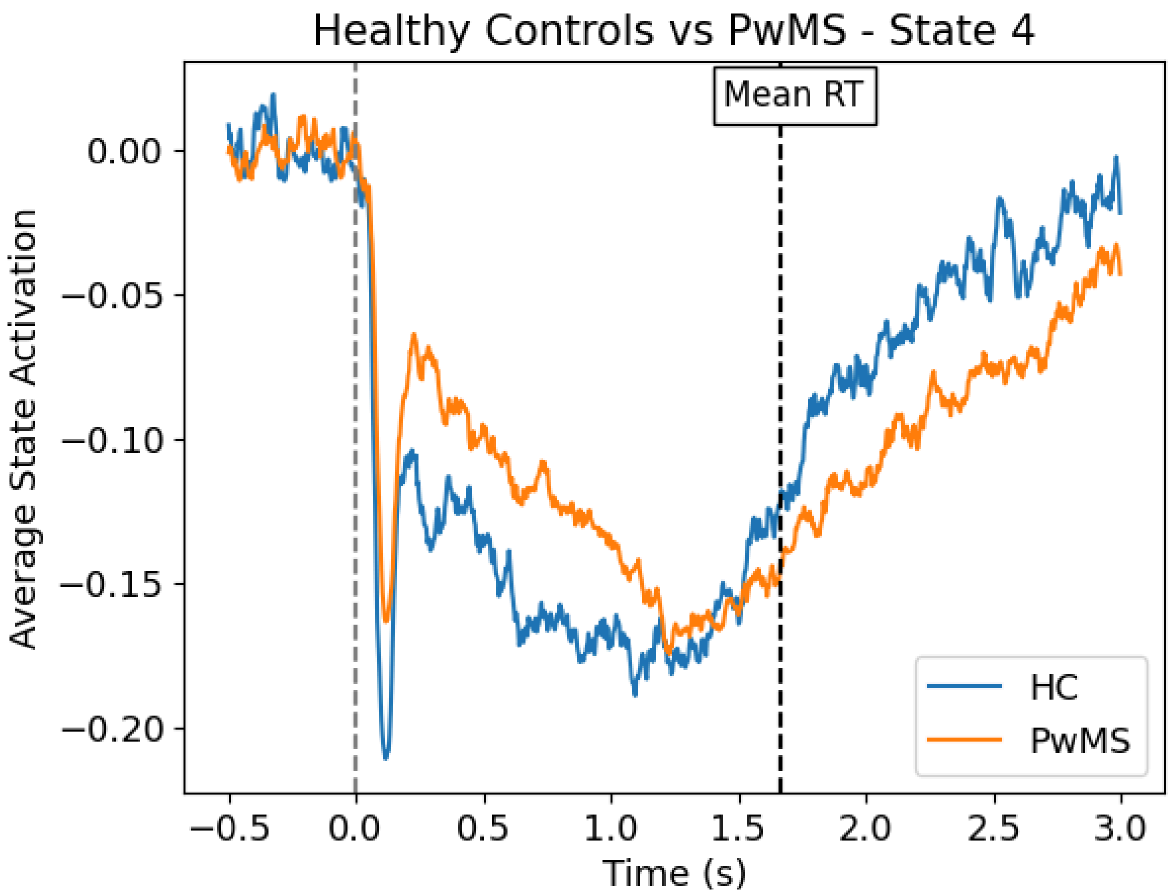
In [75]:
```
## Plot MS vs. HC per state
for i in range(n_states):
    plt.figure()
    plt.plot(t,np.mean(epochs_correct_control,axis=0)[:,i],label='HC')
    plt.plot(t,np.mean(epochs_correct_ms,axis=0)[:,i],label='PwMS')
    plt.title(f'Healthy Controls vs PwMS - State {i+1}', fontsize=15)
    plt.legend(fontsize=13)
    plt.axvline(color="gray", linestyle="--")
    plt.axvline(x=1.668, color="k", linestyle="--")   # 1,668 is the mean re
    plt.text(0.55, 0.94, 'Mean RT', fontsize = 12, bbox = dict(facecolor = '
    plt.xlabel('Time (s)', fontsize=13)
    plt.ylabel('Average State Activation', fontsize=13)
```

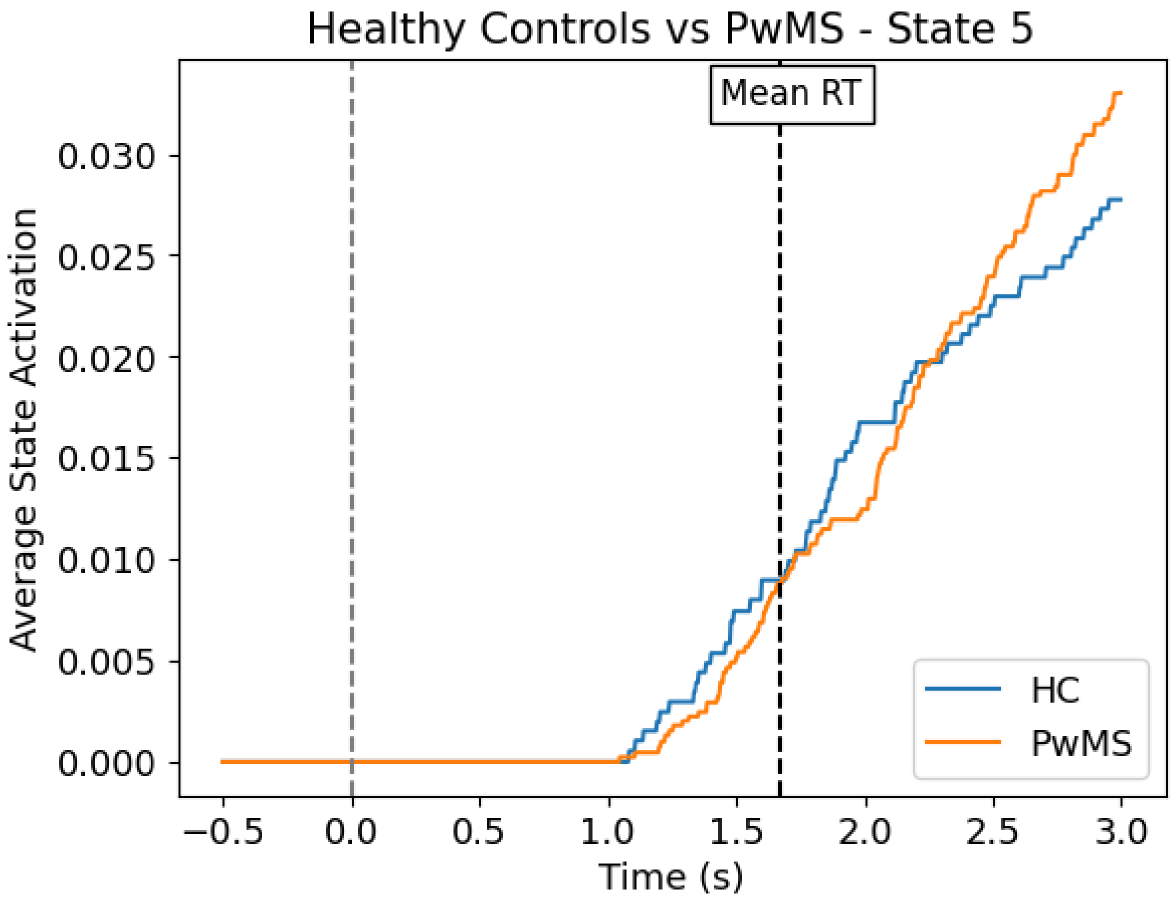
```
    plt.xticks(fontsize=13)
    plt.yticks(fontsize=13)
```

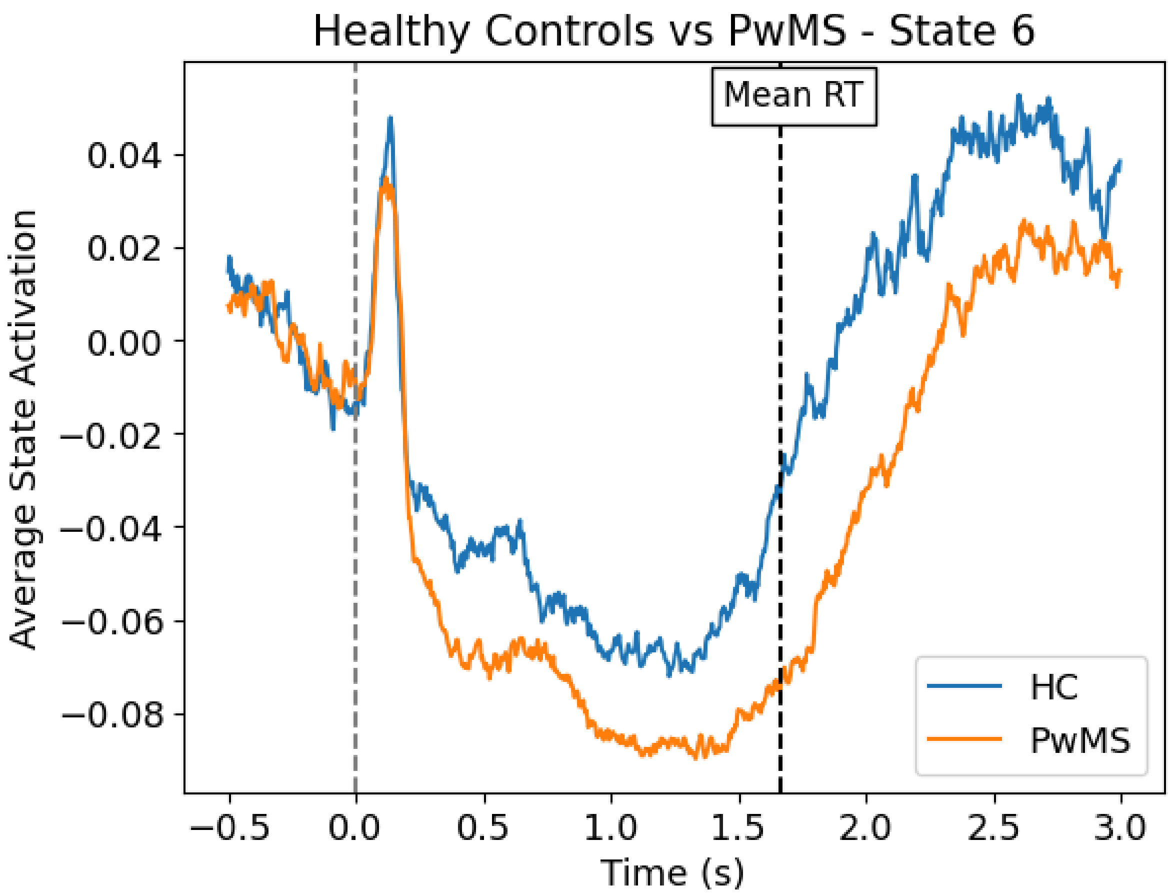


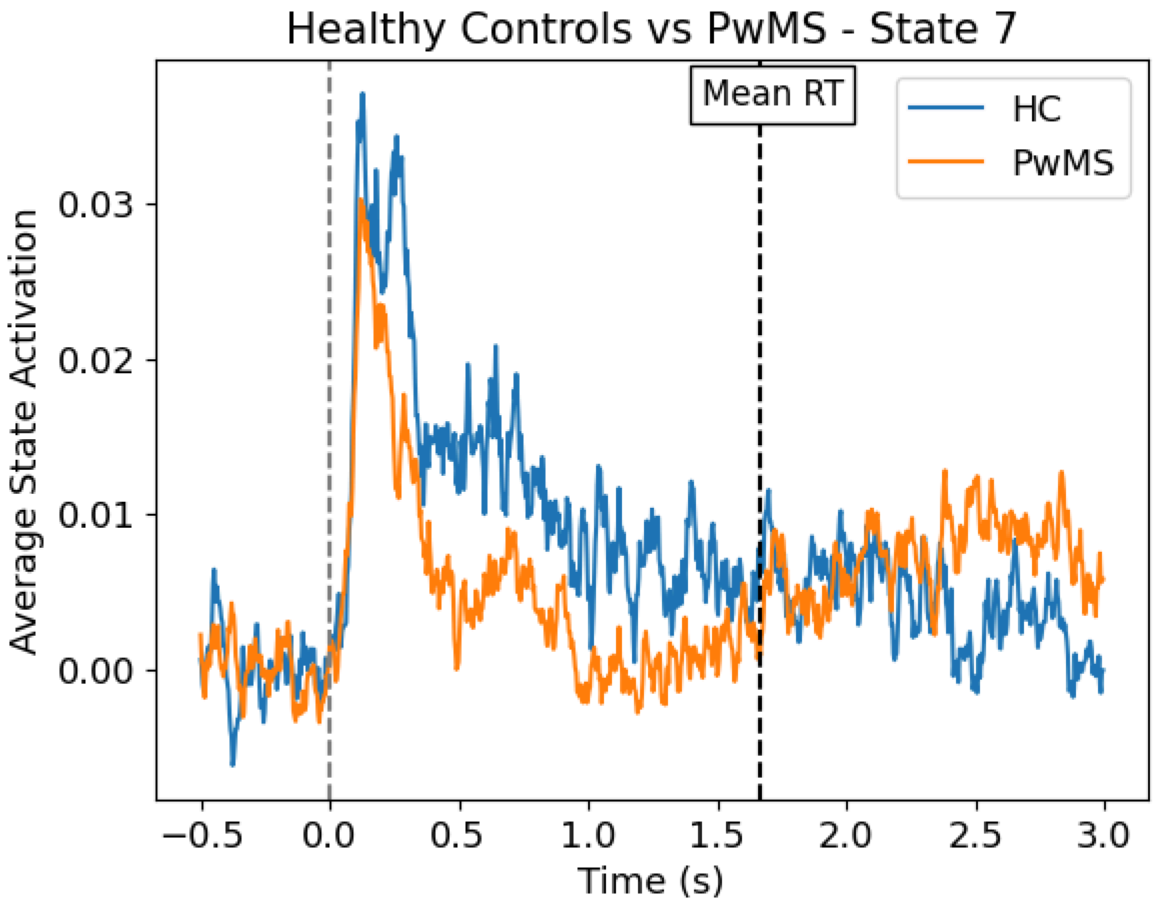


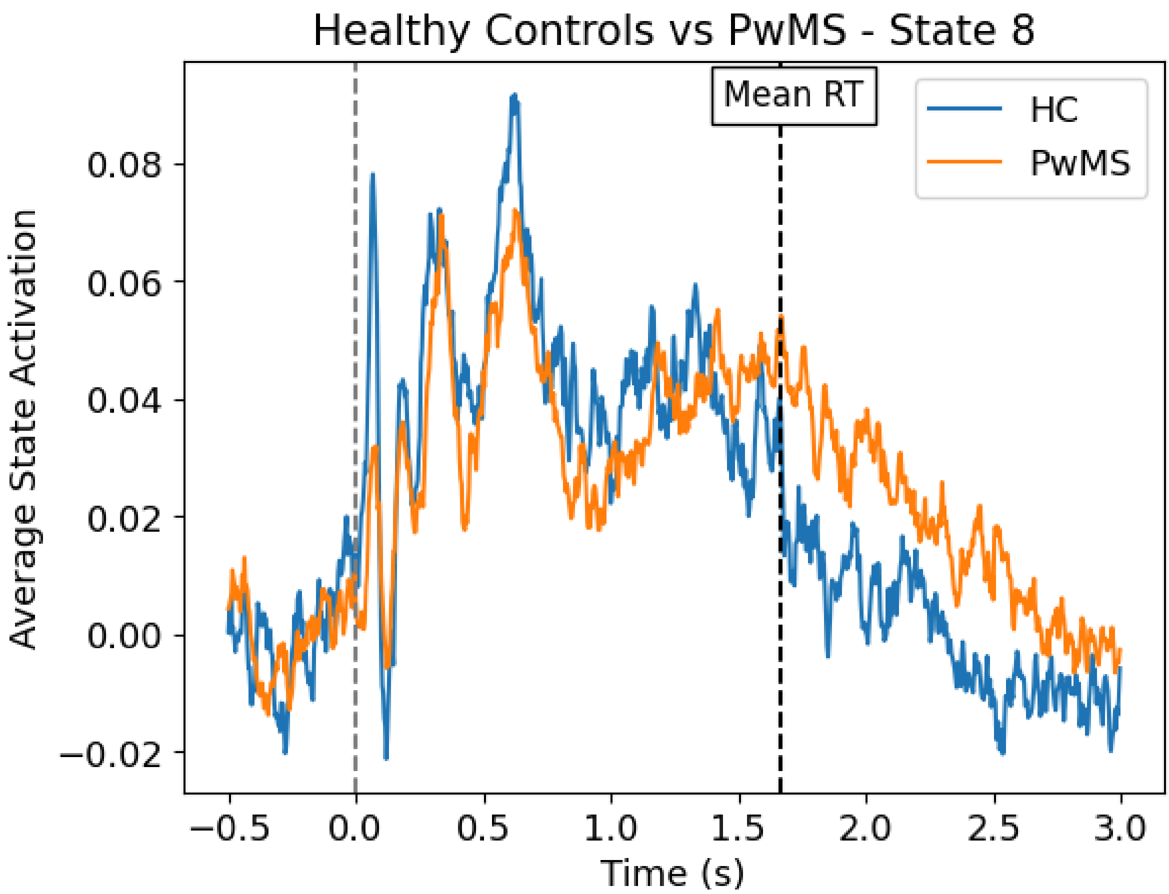

Healthy Controls vs PwMS - State 3
Mean RT
HC
PwMS
Average State Activation
Time (s)
0.4
0.3
0.2
0.1
0.0
−0.1
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0


Healthy Controls vs PwMS - State 4
Mean RT
HC
PwMS
Average State Activation
Time (s)
0.00
−0.05
−0.10
−0.15
−0.20
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0


Healthy Controls vs PwMS - State 5
Mean RT
Average State Activation
0.030
0.025
0.020
0.015
0.010
0.005
0.000
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)
HC
PwMS


Healthy Controls vs PwMS - State 6
Mean RT
Average State Activation
0.04
0.02
0.00
−0.02
−0.04
−0.06
−0.08
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)
HC
PwMS





In [76]:
```
## Max stat permutation testing for statistically significant differences
group_diff_pvals = []
for i in range(n_states):
    data_test = subj_stc_epochs[:,:,i]
    print(np.shape(data_test))
```

```
    # Do stats testing
    diff, pvalues = statistics.group_diff_max_stat_perm(
        data_test,
        assignments, # uses the group assignments from previous cell
        n_perm=1000,
    )
    group_diff_pvals.append(pvalues)
    print("Number of significant differences:", np.sum(pvalues < 0.05))
```

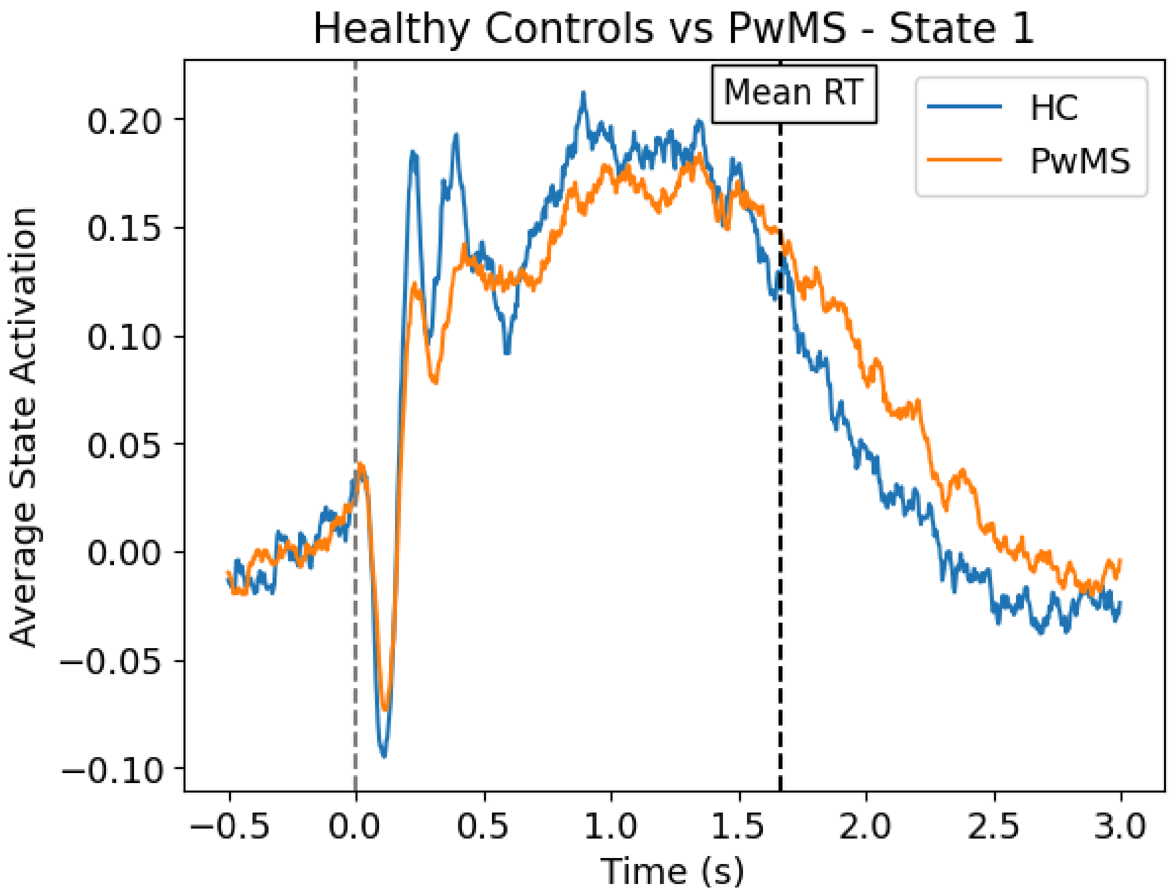
```
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
```

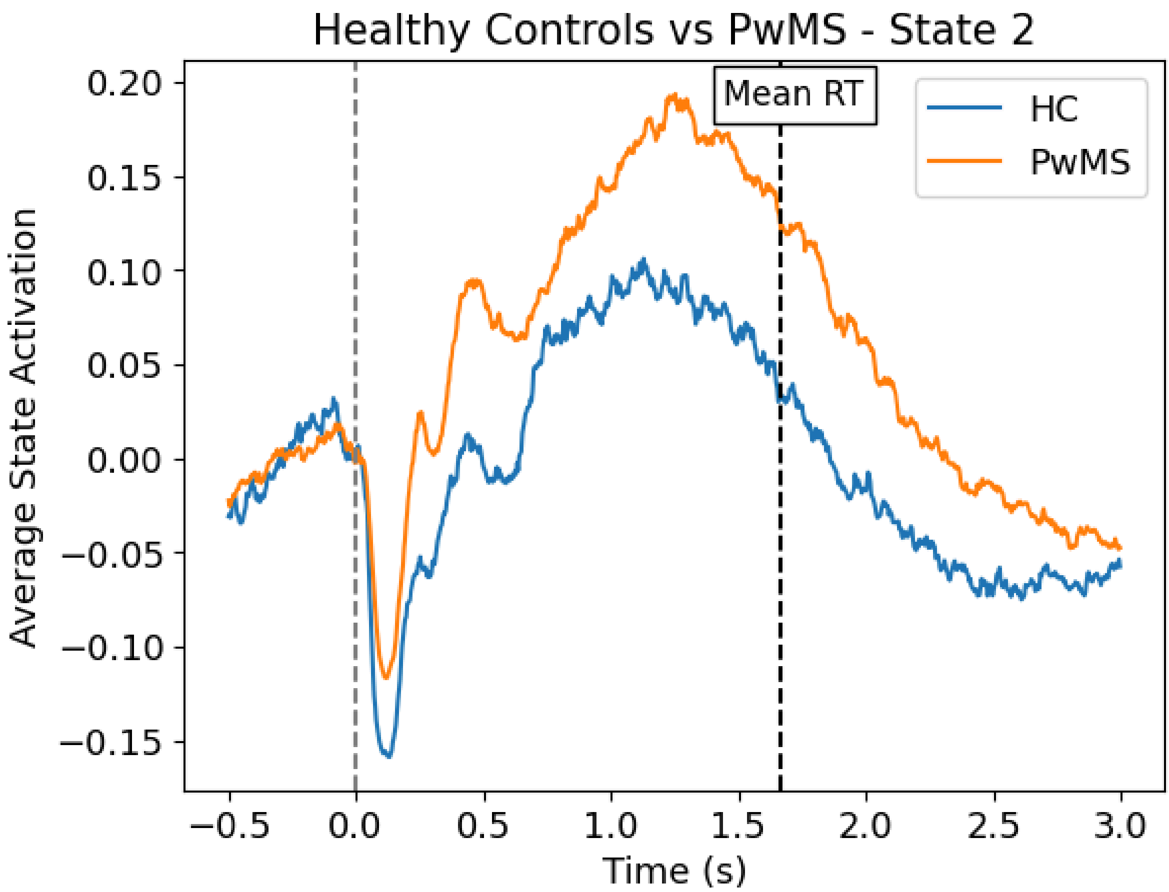
```
/home/olivierb/.local/lib/python3.9/site-packages/glmtools/fit.py:464: Ru
ntimeWarning: invalid value encountered in divide
  copes / denom,
```

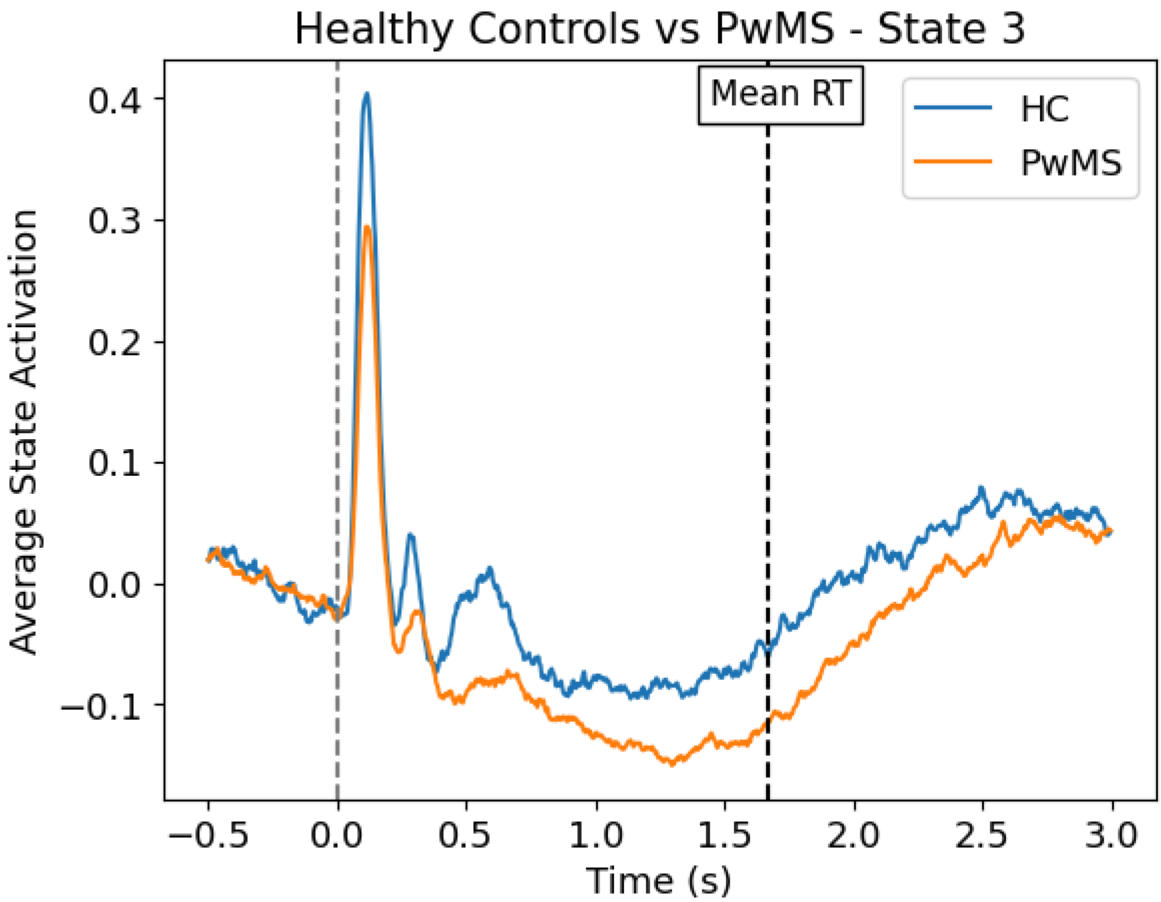
```
Using tstats as metric
Number of significant differences: 0
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 1
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
```

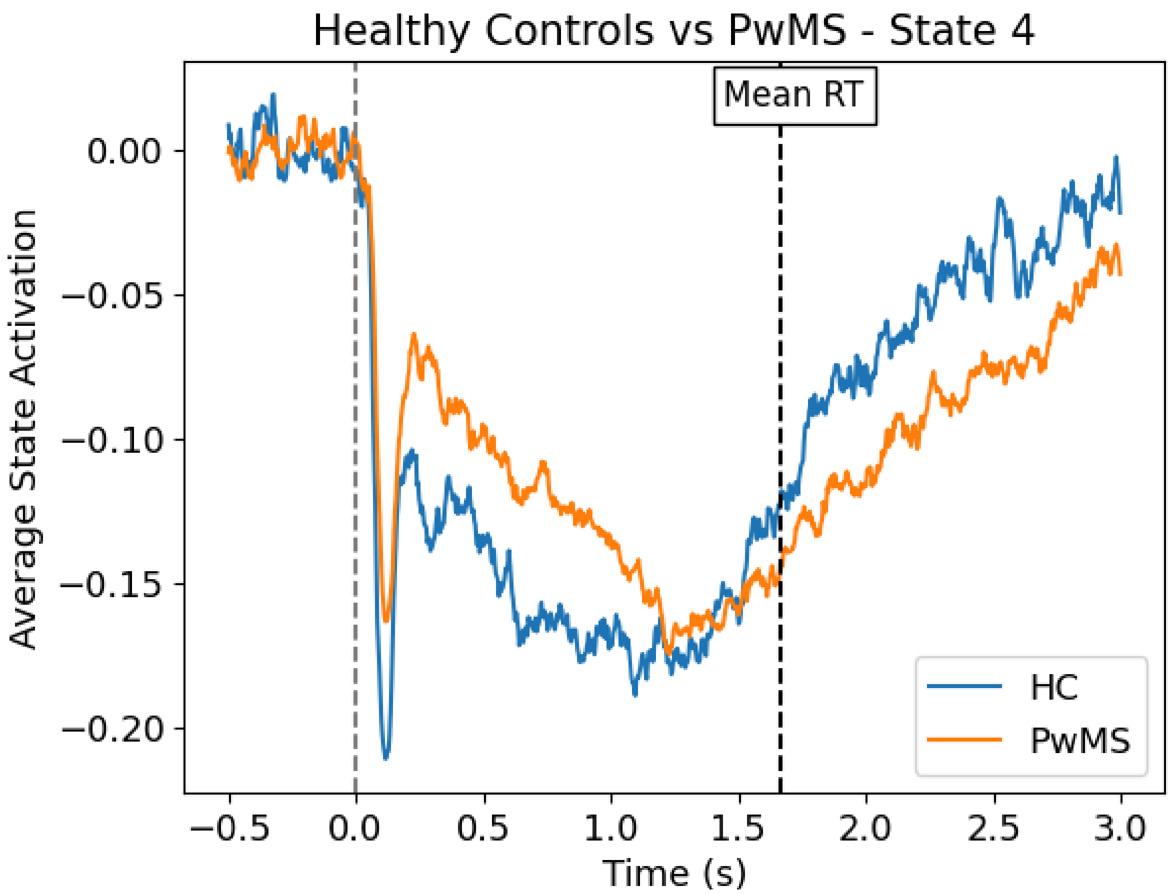
In [77]:

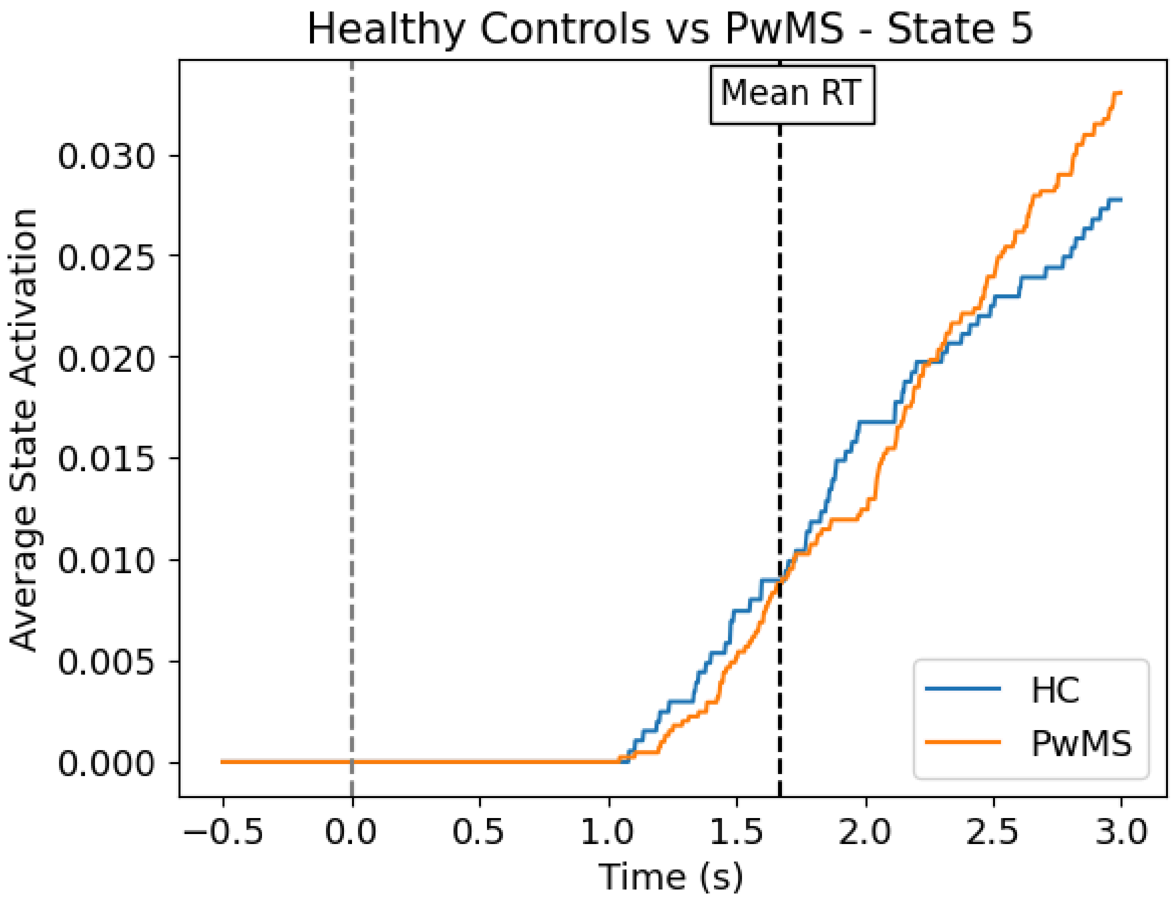
```python
from collections import OrderedDict

## Plot MS vs. HC per state and group comparison stat. sign. diff.
for i in range(n_states):
    plt.figure()
    plt.plot(t,np.mean(epochs_correct_control,axis=0)[:,i],label='HC')
    plt.plot(t,np.mean(epochs_correct_ms,axis=0)[:,i],label='PwMS')
    plt.title(f'Healthy Controls vs PwMS - State {i+1}', fontsize=15)
    plt.xlabel('Time (s)', fontsize=13)
    plt.ylabel('Average State Activation', fontsize=13)
    plt.legend(fontsize=13)
    plt.axvline(color="gray", linestyle="--")
    plt.text(0.55, 0.94, 'Mean RT', fontsize = 12, bbox = dict(facecolor = '
    plt.xticks(fontsize=13)
    plt.yticks(fontsize=13)

    significant = group_diff_pvals[i] < 0.05
    sig_times = t[significant]
    draw = min(np.min(np.mean(epochs_correct_control,axis=0)[:,i]), np.min(r
    if len(sig_times) > 0:
        dt = t[1] - t[0]
        y = -0.025 + i * 0.01 + draw                 # this value needs to b
        for st in sig_times:
            plt.plot((st - dt, st + dt), (y, y), linewidth=4, color='g', lab

        # StackOverflow fix to remove duplicate labels (due to ex. a for loo
        handles, labels = plt.gca().get_legend_handles_labels()
        by_label = OrderedDict(zip(labels, handles))
        plt.legend(by_label.values(), by_label.keys())

    plt.axvline(x=1.668, color="k", linestyle="--")   # 1,668 is the mean re
```

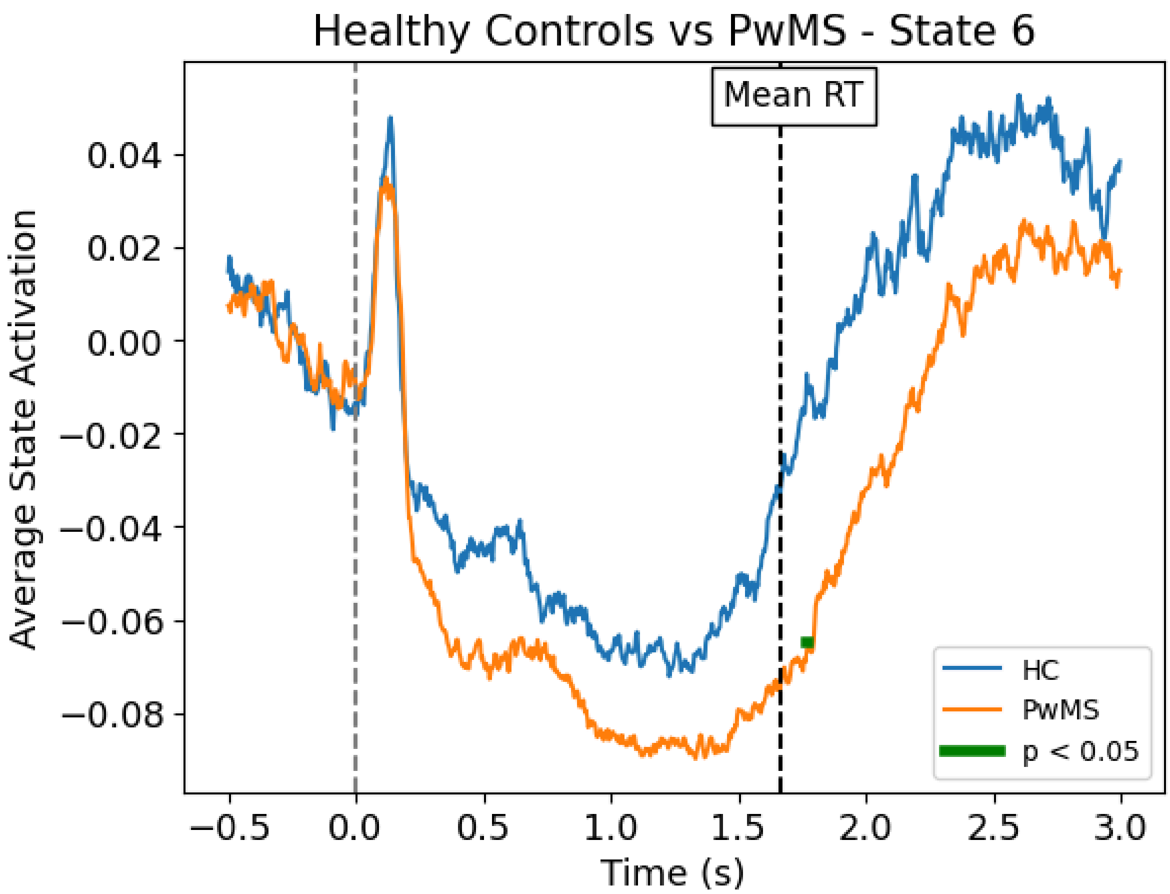

Healthy Controls vs PwMS - State 1
Mean RT
HC
PwMS
Average State Activation
Time (s)
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0

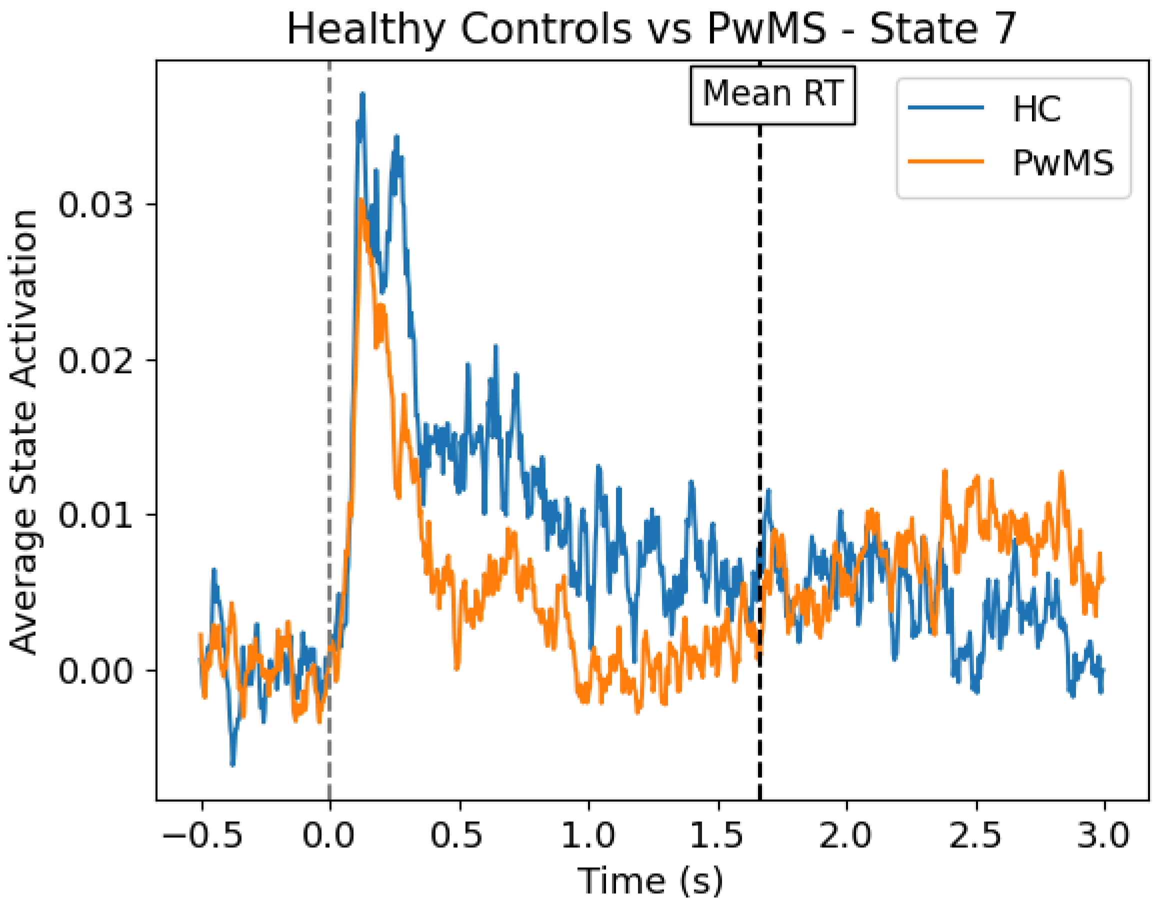

Healthy Controls vs PwMS - State 2
Mean RT
HC
PwMS
Average State Activation
Time (s)
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0

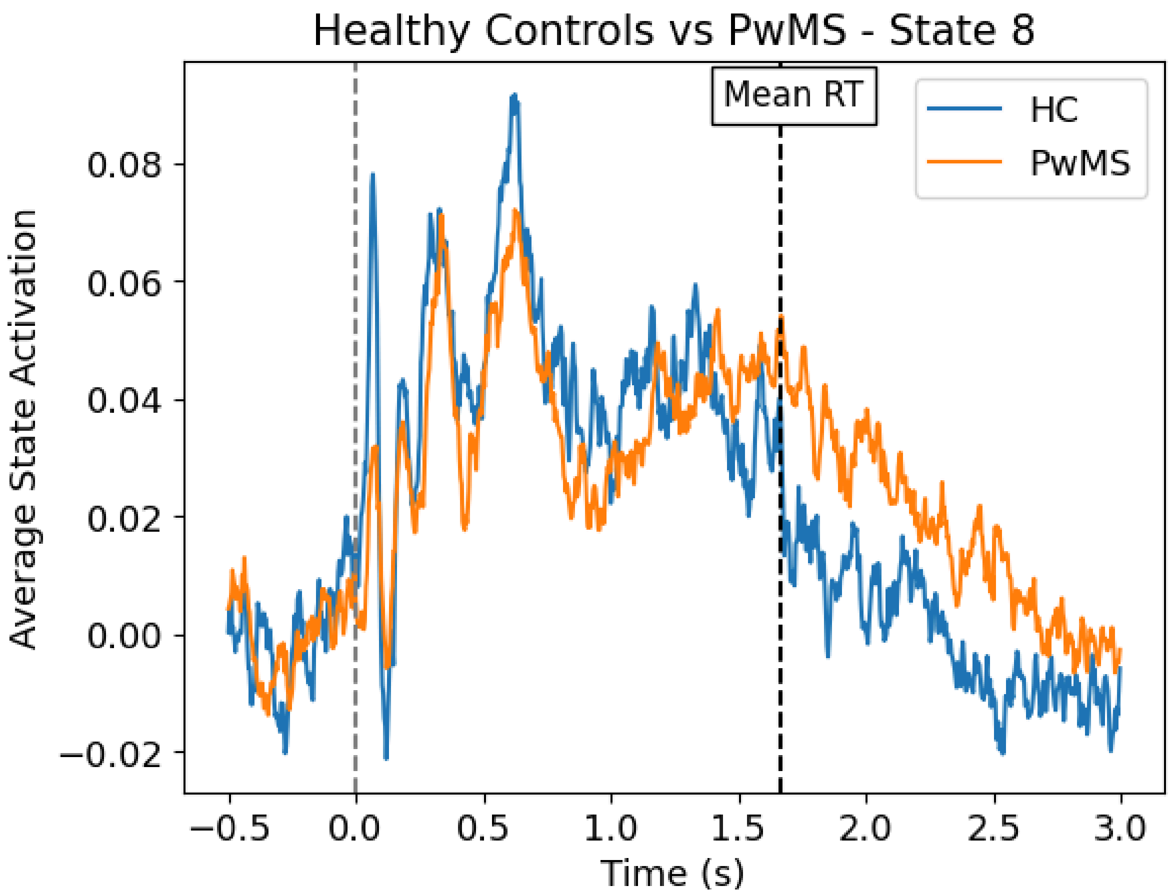

Healthy Controls vs PwMS - State 3
Mean RT
HC
PwMS
Average State Activation
0.4
0.3
0.2
0.1
0.0
−0.1
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Healthy Controls vs PwMS - State 4
Mean RT
HC
PwMS
Average State Activation
0.00
−0.05
−0.10
−0.15
−0.20
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Healthy Controls vs PwMS - State 5
Mean RT
Average State Activation
0.030
0.025
0.020
0.015
0.010
0.005
0.000
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)
HC
PwMS


Healthy Controls vs PwMS - State 6
Mean RT
Average State Activation
0.04
0.02
0.00
−0.02
−0.04
−0.06
−0.08
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)
HC
PwMS
p < 0.05





For INcorrect trials

In [78]:
```
# Extract correct & incorrect trials seperately
timings_filtered_correct = [event_indices_filtered[sub][0] for sub in range(
timings_filtered_incorrect = [event_indices_filtered[sub][1] for sub in rang
```

Aligning the state time course to the event timings

In [79]:
```
## 1)
## Pad-locking of alpha (alligning with original MEG timecourse)
# n_embeddings=15 -> 7 (= 15/2 - 1) datapoints are lost from the start and e
timings_filtered_incorrect_pad = [v - 7 for v in timings_filtered_incorrect]

## 2)
# Substracting this value might lead to the first event occuring as a negati
# This corresponds to an event we chopped off when we time-delay embedded

# Remove events that we missed due to time-delay embedding
timings_filtered_incorrect_pad = [v[v > 0] for v in timings_filtered_incorre

## 3)
# We also lose a few data points from the end of each subject's time series
# -> Let's remove events that we cut off when we separated the training data
timings_filtered_incorrect_pad = [v[v < s.shape[0]] for v,s in zip(timings_f
#print(event_indices_tde)
```

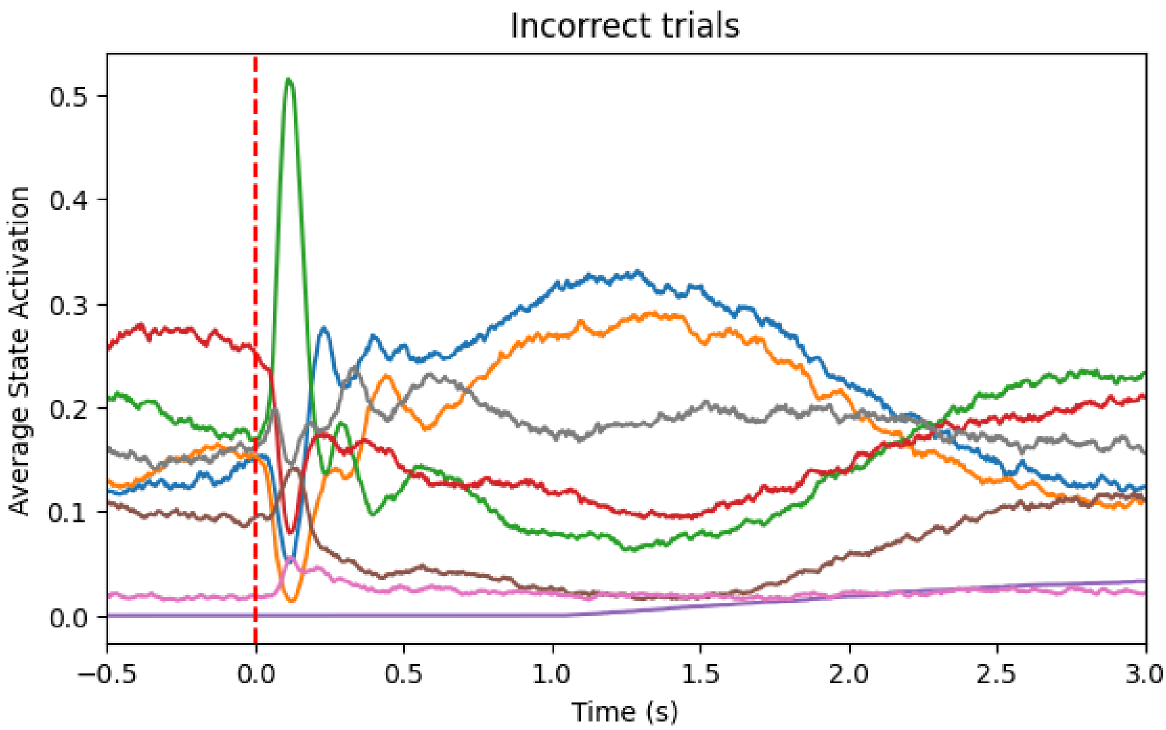
Epoch

In [80]:
```
# Epoch around events
stc_epochs = []
for s, v in zip(stc, timings_filtered_incorrect_pad):                    # filt
    stc_epochs.append(task.epoch(s, v, pre=125, post=750))

# Concatenate over subjects
concat_stc_epochs = np.concatenate(stc_epochs)
print(concat_stc_epochs.shape)

# Average over epochs
avg_stc_epoch = np.nanmean(concat_stc_epochs, axis=0)
print(avg_stc_epoch.shape)
```

```
(6858, 875, 8)
(875, 8)
```

In [81]:
```
n_states = avg_stc_epoch.shape[1]  # number of states
t = (np.arange(avg_stc_epoch.shape[0]) - 250/2) / fs  # time axis

# Plot the visual task
fig, ax = plotting.plot_line(
    [t] * n_states,
    avg_stc_epoch.T,
    x_range=[-0.5, 3],
    x_label="Time (s)",
    y_label="Average State Activation",
    title="Incorrect trials"
)
ax.axvline(color="r", linestyle="--")
```

Out[81]:
```
<matplotlib.lines.Line2D at 0x7fd300256bb0>
```

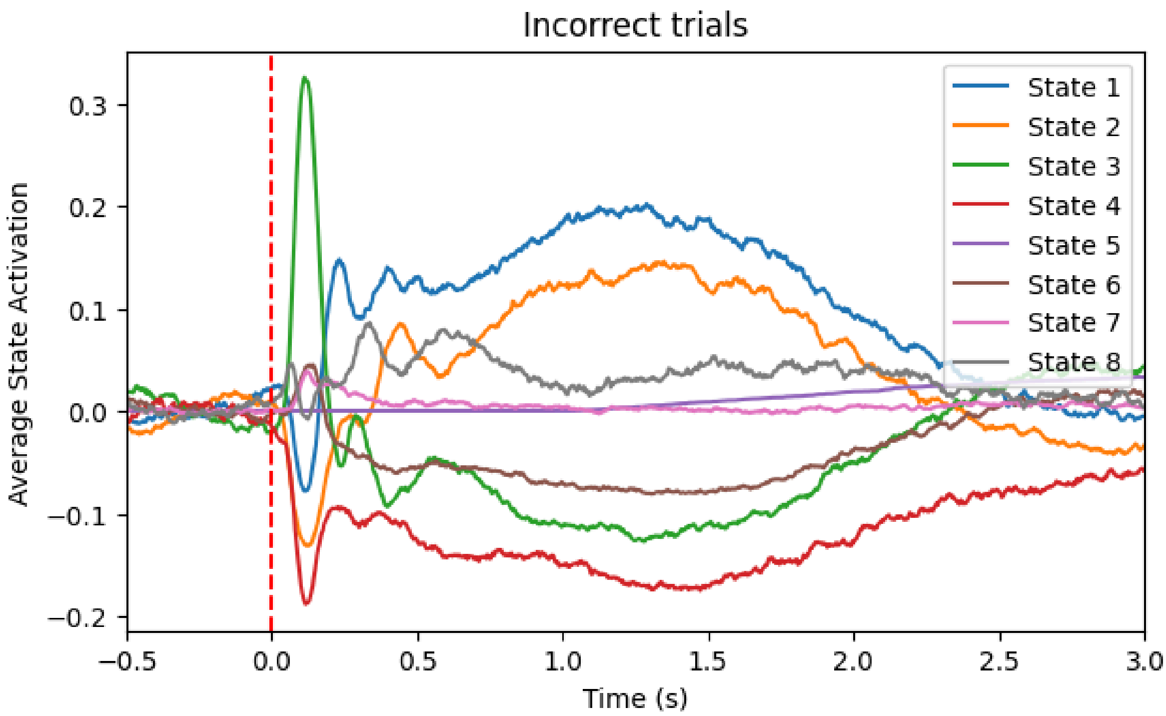


In [82]:

```
# Calculate the baseline
pre = 125  # number of samples before the event
base_corr = np.nanmean(avg_stc_epoch[:pre], axis=0, keepdims=True)

# Remove it from the epoched state time courses
corr_avg_stc_epoch = avg_stc_epoch - base_corr

# Plot the visual task
fig, ax = plotting.plot_line(
    [t] * n_states,
    corr_avg_stc_epoch.T,
    labels=[f"State {i}" for i in range(1, n_states + 1)],
    x_range=[-0.5, 3],
    x_label="Time (s)",
    y_label="Average State Activation",
    title='Incorrect trials'
)
ax.axvline(color="r", linestyle="--")
```

Out[82]:

```
<matplotlib.lines.Line2D at 0x7fd343adb490>
```

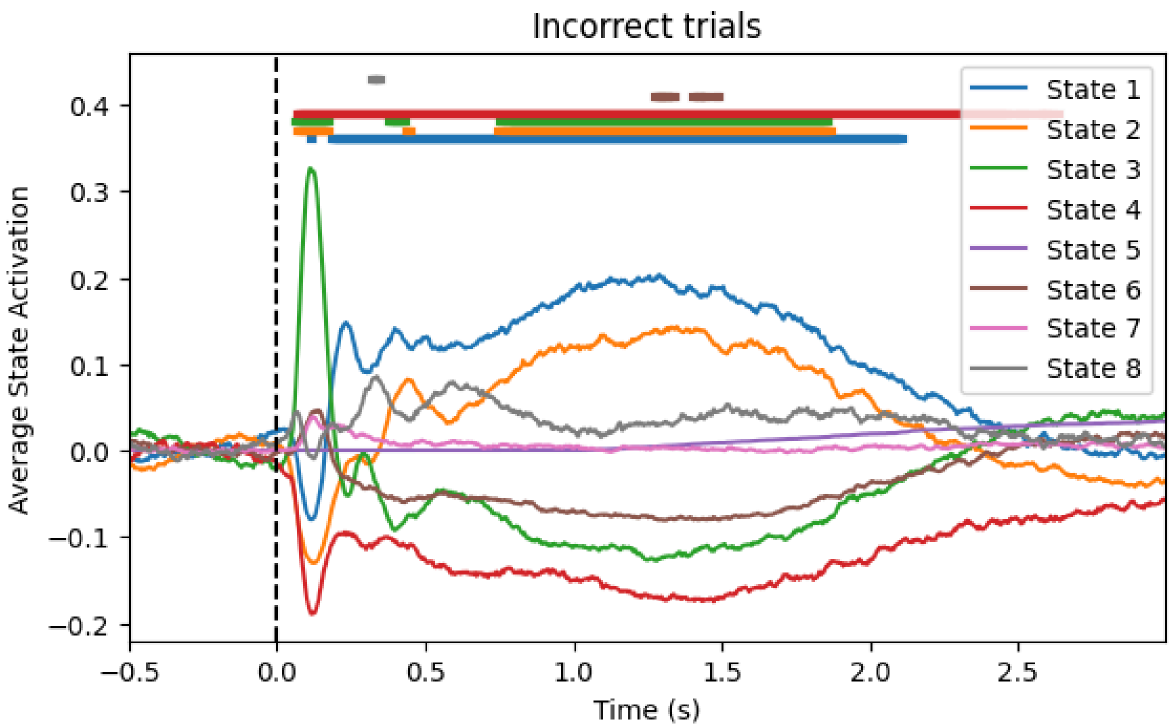


In [83]:
```
from osl_dynamics.analysis import statistics

# We already have the trial specific epochs separated by subjects in stc_epo
# we just need to average each subject's trials separately
subj_stc_epochs = []
for epochs in stc_epochs:
    subj_stc_epochs.append(np.nanmean(epochs, axis=0))
subj_stc_epochs = np.array(subj_stc_epochs)
print(subj_stc_epochs.shape)

# Baseline correct using the samples before the event
subj_stc_epochs -= np.mean(subj_stc_epochs[:, :pre], axis=1, keepdims=True)

# Calculate p-values
pvalues = statistics.evoked_response_max_stat_perm(subj_stc_epochs, n_perm=1
print(pvalues.shape)

# Do any time points/states come out as significant?
print("Number of time points with at least 1 state with p-value < 0.05:", np
```

```
(110, 875, 8)
Permuting contrast <class 'glmtools.design.Contrast'>(Mean,MainEffect) wi
th mode=sign-flip
        Computing 1000 permutations
        Taking max-stat across ['time', 'features 1'] dimensions
Using copes as metric
(875, 8)
Number of time points with at least 1 state with p-value < 0.05: 626
```

In [84]:
```
plotting.plot_evoked_response(
    t,
    np.mean(subj_stc_epochs, axis=0),
    pvalues,
    labels=[f"State {i + 1}" for i in range(subj_stc_epochs.shape[-1])],
    significance_level=0.05,
    x_label="Time (s)",
    y_label="Average State Activation",
    title="Incorrect trials",
)
```

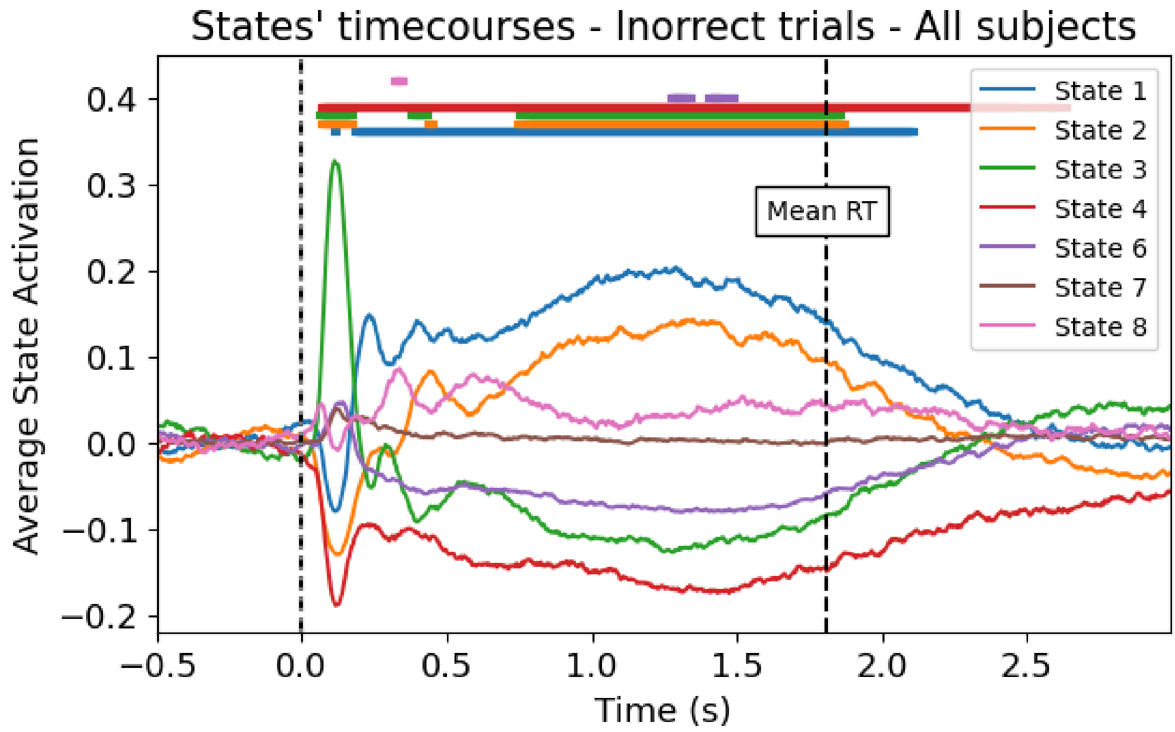
Out[84]:
```
(<Figure size 700x400 with 1 Axes>,
 <Axes: title={'center': 'Incorrect trials'}, xlabel='Time (s)', ylabel
='Average State Activation'>)
```



In [85]:
```
print(np.shape(subj_stc_epochs))

subj_stc_epochs_NEW = subj_stc_epochs[:][:,:, np.array([True, True, True, Tr
print(subj_stc_epochs_NEW.shape)

pvalues_NEW = pvalues[:][:, np.array([True, True, True, True, False, True, T

plotting.plot_evoked_response(
    t,
    np.mean(subj_stc_epochs_NEW, axis=0),
    pvalues_NEW,
    labels=[f"State {i + 1}" for i in [0,1,2,3,5,6,7]],
    significance_level=0.05,
    x_label="Time (s)",
    y_label="Average State Activation",
    title="States' timecourses - Incorrect trials - All subjects"
)
plt.axvline(color="gray", linestyle="dotted")
plt.axvline(x=1.81, color="k", linestyle="--")   # 1,668 is the mean reactio
plt.text(1.60, 0.26, 'Mean RT', fontsize = 10, bbox = dict(facecolor = 'whit

plt.xlabel("Time (s)", fontsize=13)
plt.ylabel("Average State Activation", fontsize=13)
plt.xticks(fontsize=13)
plt.yticks(fontsize=13)
plt.title("States' timecourses - Inorrect trials - All subjects", fontsize=1
```

```
(110, 875, 8)
(110, 875, 7)
```

Out[85]:
```
Text(0.5, 1.0, "States' timecourses - Inorrect trials - All subjects")
```

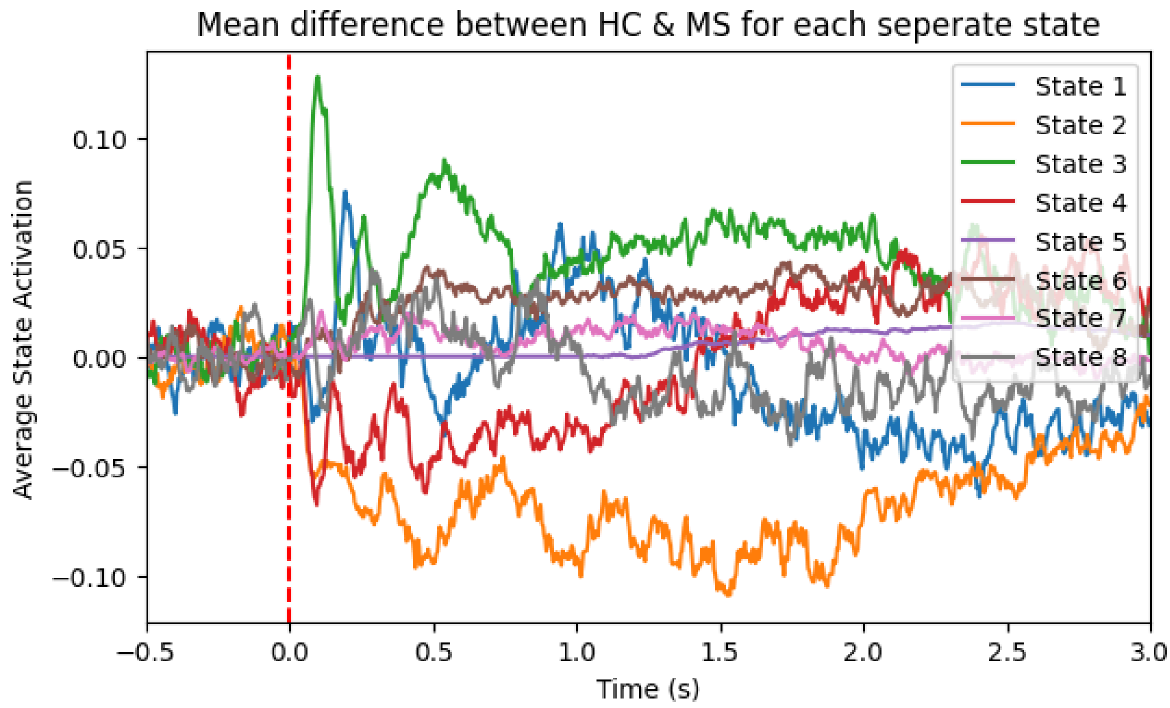


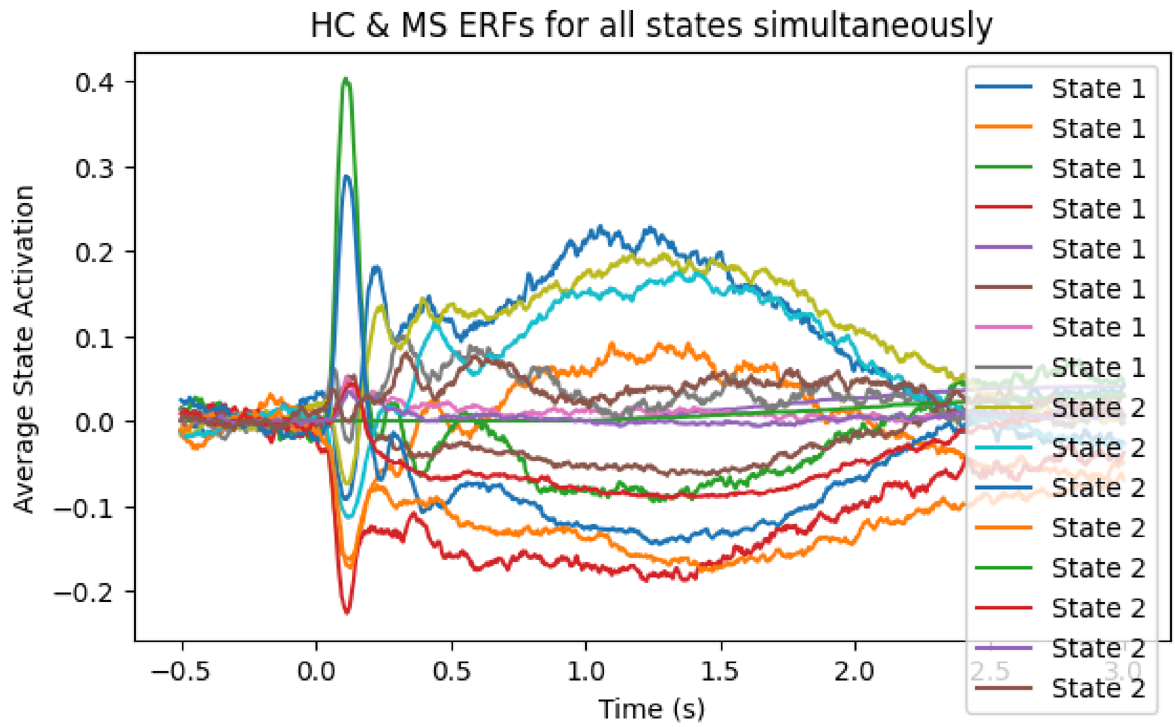
Group comparison (HC vs. MS)

In [86]:

```
# ex. for state 1
epochs_incorrect_control = [subj_stc_epochs[sub] for sub in range(len(subj_s
epochs_incorrect_ms = [subj_stc_epochs[sub] for sub in range(len(subj_stc_ep

print(np.shape(epochs_incorrect_control))
print(np.shape(epochs_incorrect_ms))

group_diff = []
for i in range(n_states):
    group_diff.append(np.mean(epochs_incorrect_control,axis=0)[:,i] - np.mea

# Plot the visual task
fig, ax = plotting.plot_line(
    [t] * n_states,
    np.array(group_diff),
    labels=[f"State {i}" for i in range(1, n_states + 1)],
    x_range=[-0.5, 3],
    x_label="Time (s)",
    y_label="Average State Activation",
    title = 'Mean difference between HC & MS for each seperate state'
)
ax.axvline(color="r", linestyle="--")

plotting.plot_line(
    [t,t],
    [np.mean(epochs_incorrect_control, axis=0),np.mean(epochs_incorrect_ms,
    labels=[f"State {i + 1}" for i in range(2)],
    x_label="Time (s)",
    y_label="Average State Activation",
    title = 'HC & MS ERFs for all states simultaneously'
)

print(np.shape(np.mean(epochs_incorrect_control,axis=0)))
```

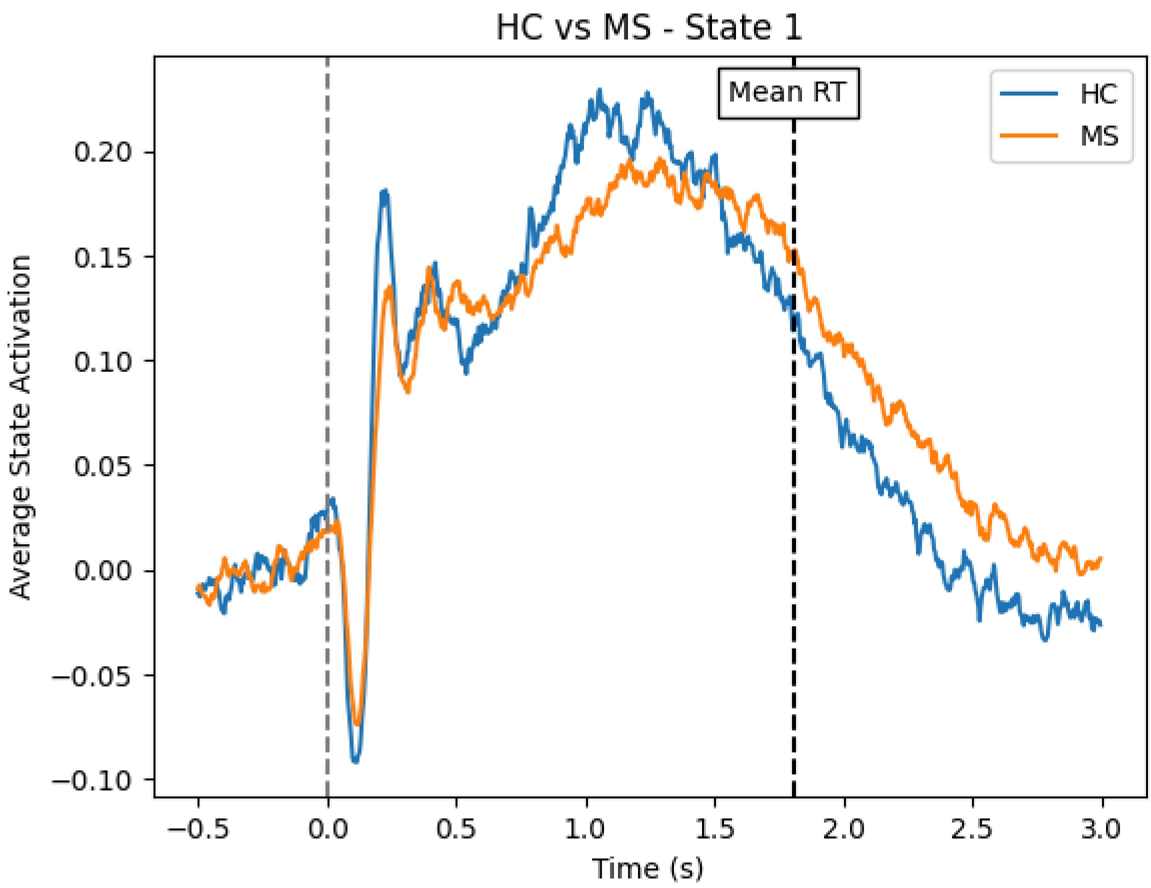
```
(37, 875, 8)
(73, 875, 8)
(875, 8)
```

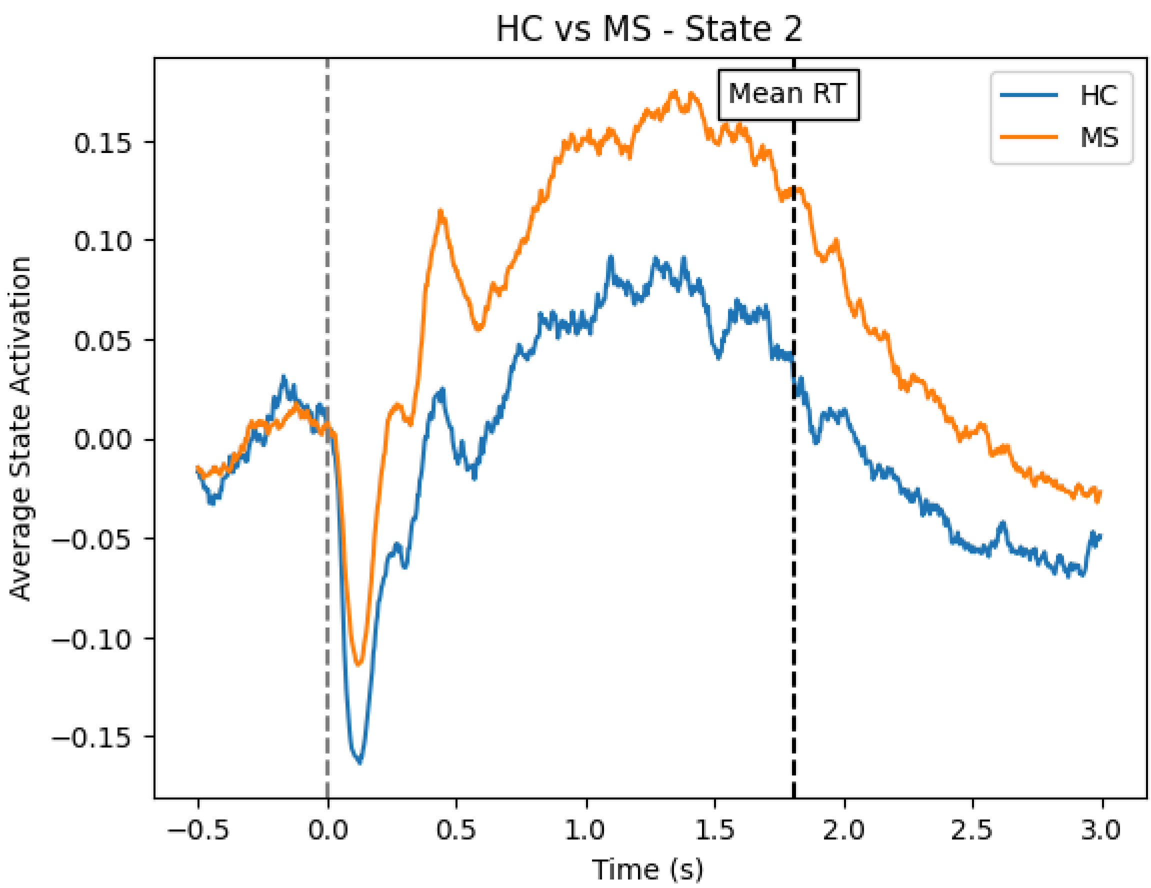


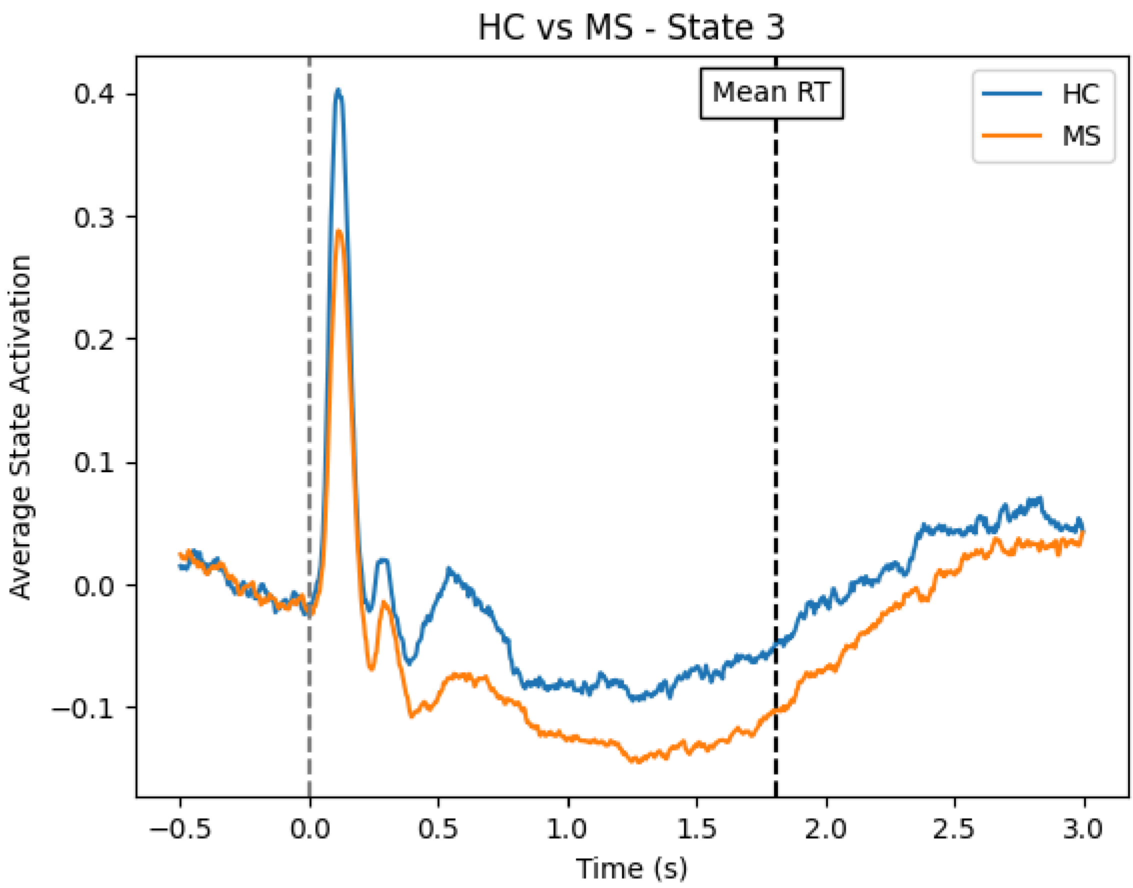


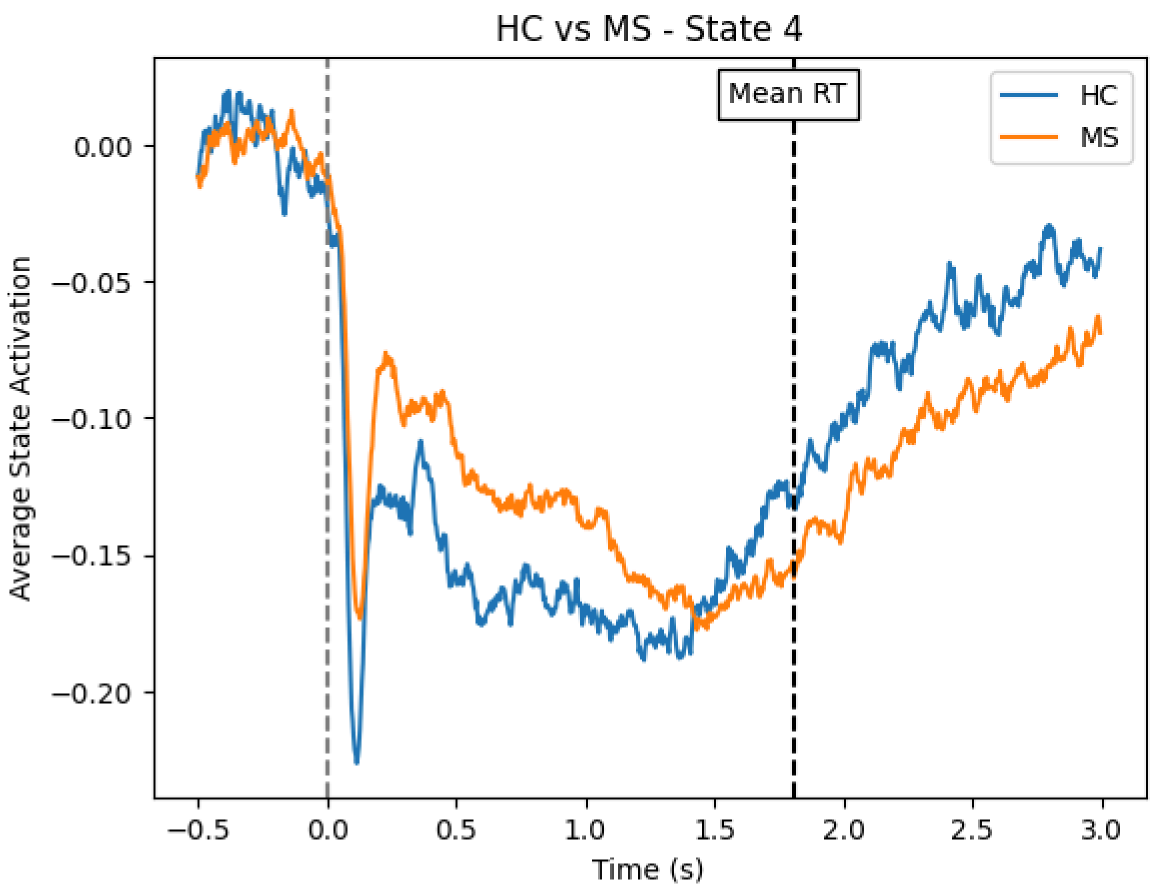
In [87]:

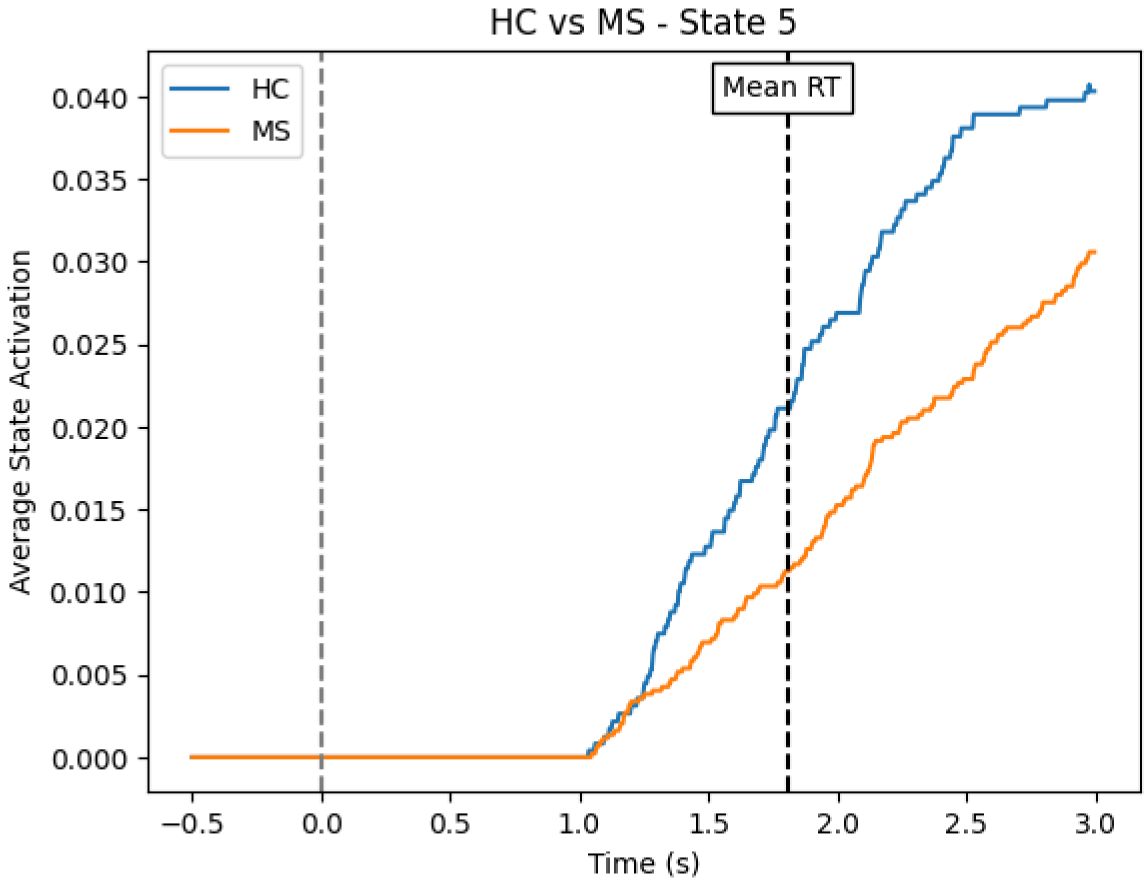
```
## Plot MS vs. HC per state
for i in range(n_states):
    plt.figure()
    plt.plot(t,np.mean(epochs_incorrect_control,axis=0)[:,i],label='HC')
    plt.plot(t,np.mean(epochs_incorrect_ms,axis=0)[:,i],label='MS')
    plt.title(f'HC vs MS - State {i+1}')
    plt.legend()
    plt.axvline(color="gray", linestyle="--")
    plt.axvline(x=1.81, color="k", linestyle="--")   # 1,668 is the mean rea
    plt.text(0.58, 0.94, 'Mean RT', fontsize = 10, bbox = dict(facecolor = '
    plt.xlabel('Time (s)')
    plt.ylabel('Average State Activation')
```

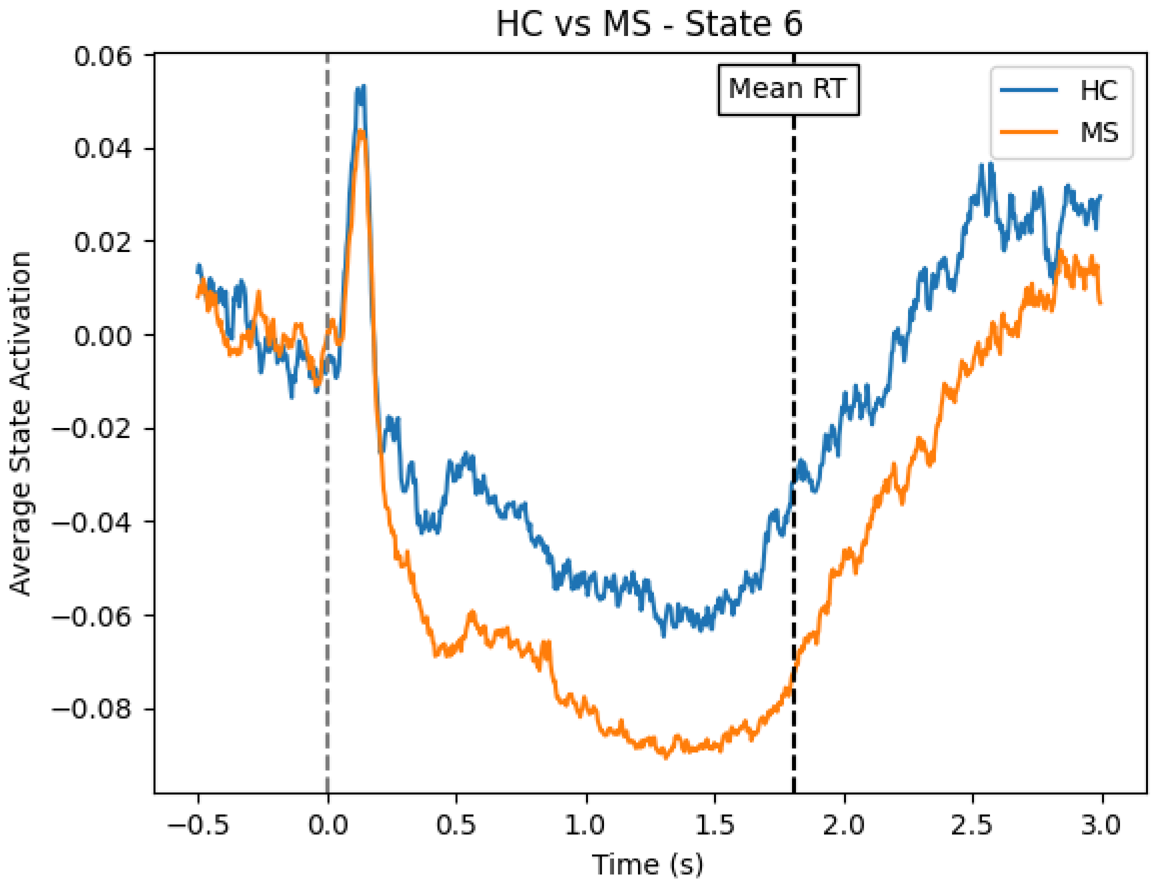

HC vs MS - State 1
Mean RT
HC
MS
Average State Activation
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)

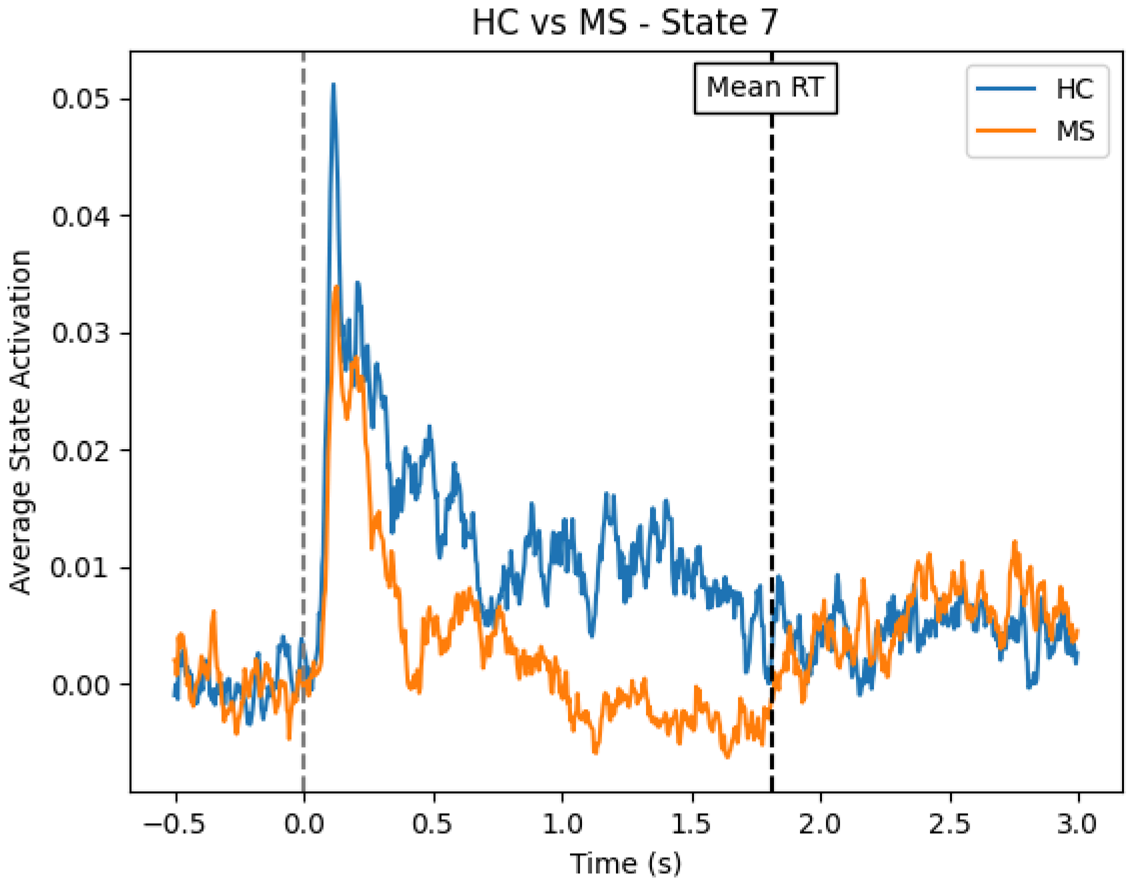

HC vs MS - State 2
Mean RT
HC
MS
Average State Activation
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)

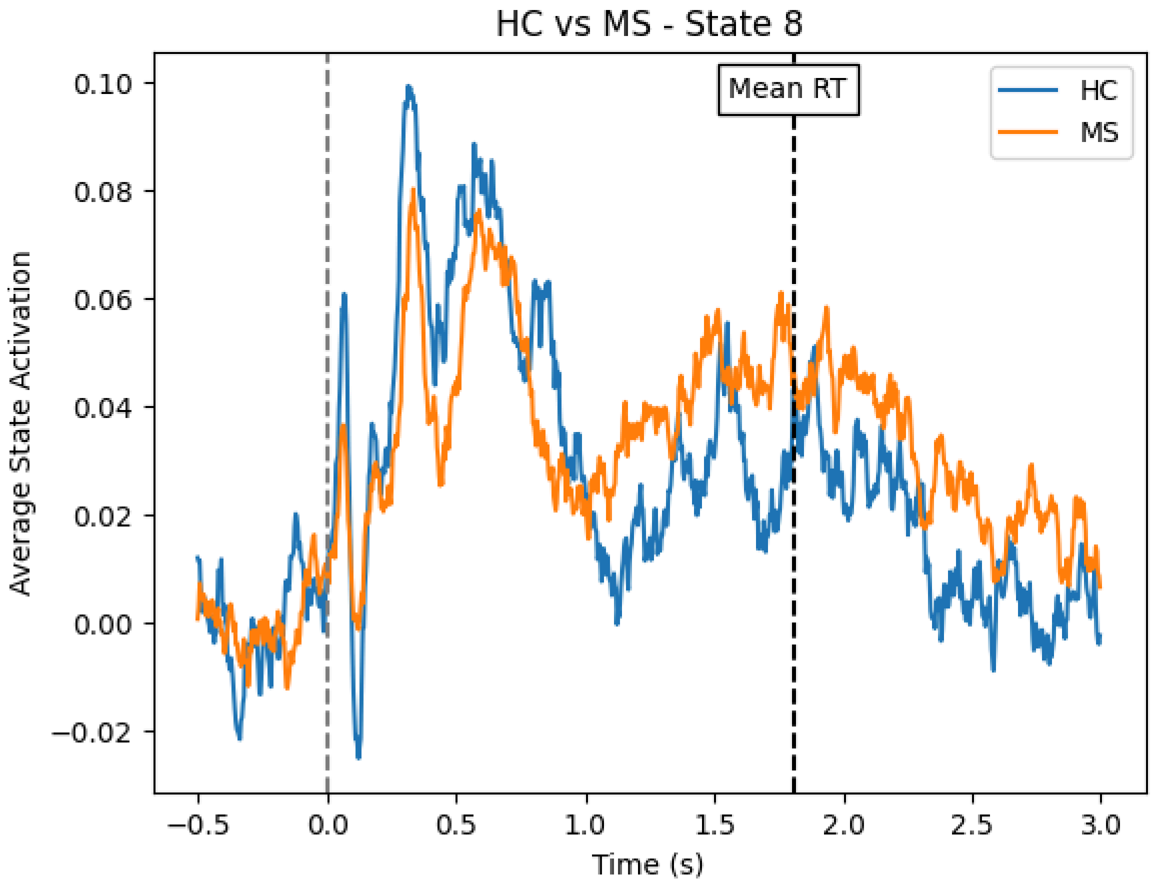

HC vs MS - State 3
Mean RT
HC
MS
Average State Activation
0.4
0.3
0.2
0.1
0.0
−0.1
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


HC vs MS - State 4
Mean RT
HC
MS
Average State Activation
0.00
−0.05
−0.10
−0.15
−0.20
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


HC vs MS - State 5
HC
MS
Mean RT
Average State Activation
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


HC vs MS - State 6
Mean RT
HC
MS
Average State Activation
0.06
0.04
0.02
0.00
−0.02
−0.04
−0.06
−0.08
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)





In [88]:
```
## Max stat permutation testing for statistically significant differences
group_diff_pvals = []
for i in range(n_states):
    data_test = subj_stc_epochs[:,:,i]
    print(np.shape(data_test))

    # Do stats testing
```

```
    diff, pvalues = statistics.group_diff_max_stat_perm(
        data_test,
        assignments, # uses the group assignments from previous cell
        n_perm=1000,
    )
    group_diff_pvals.append(pvalues)
    print("Number of significant differences:", np.sum(pvalues < 0.05))
```

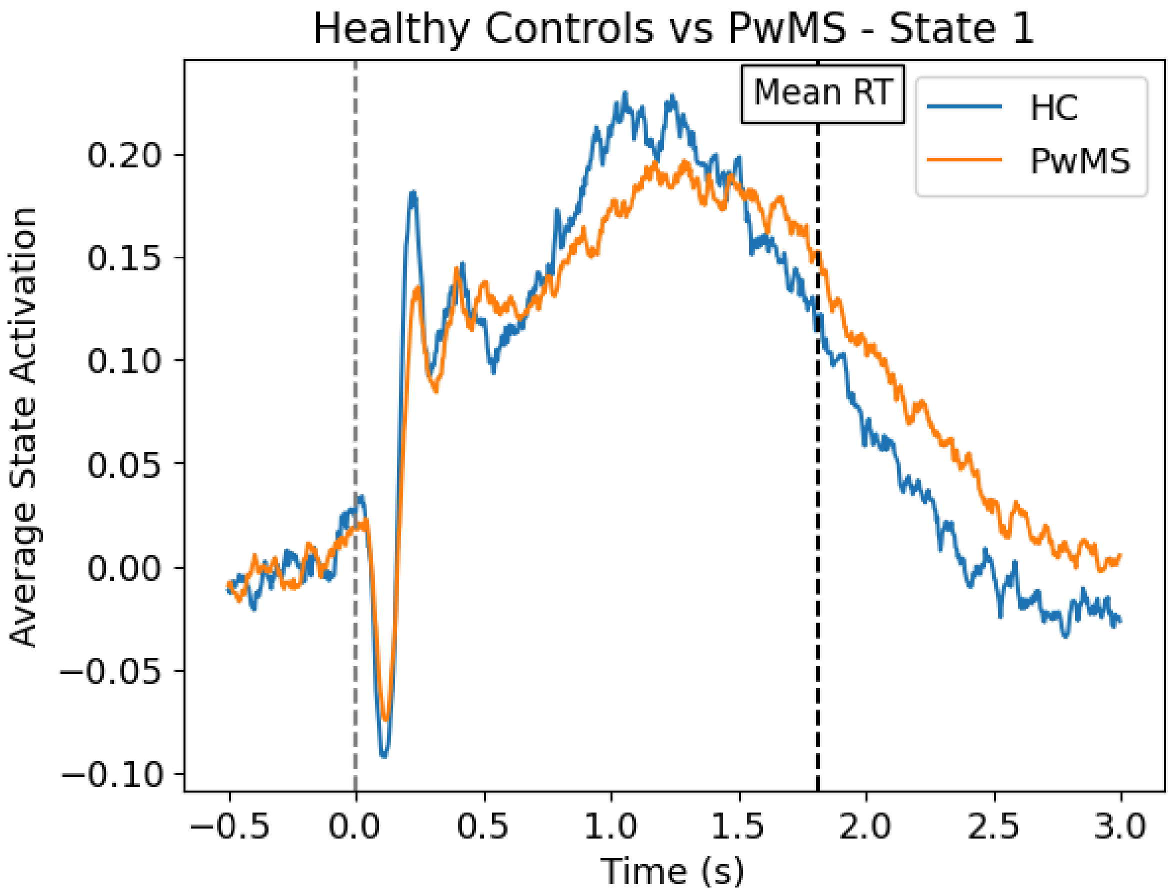
```
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
```

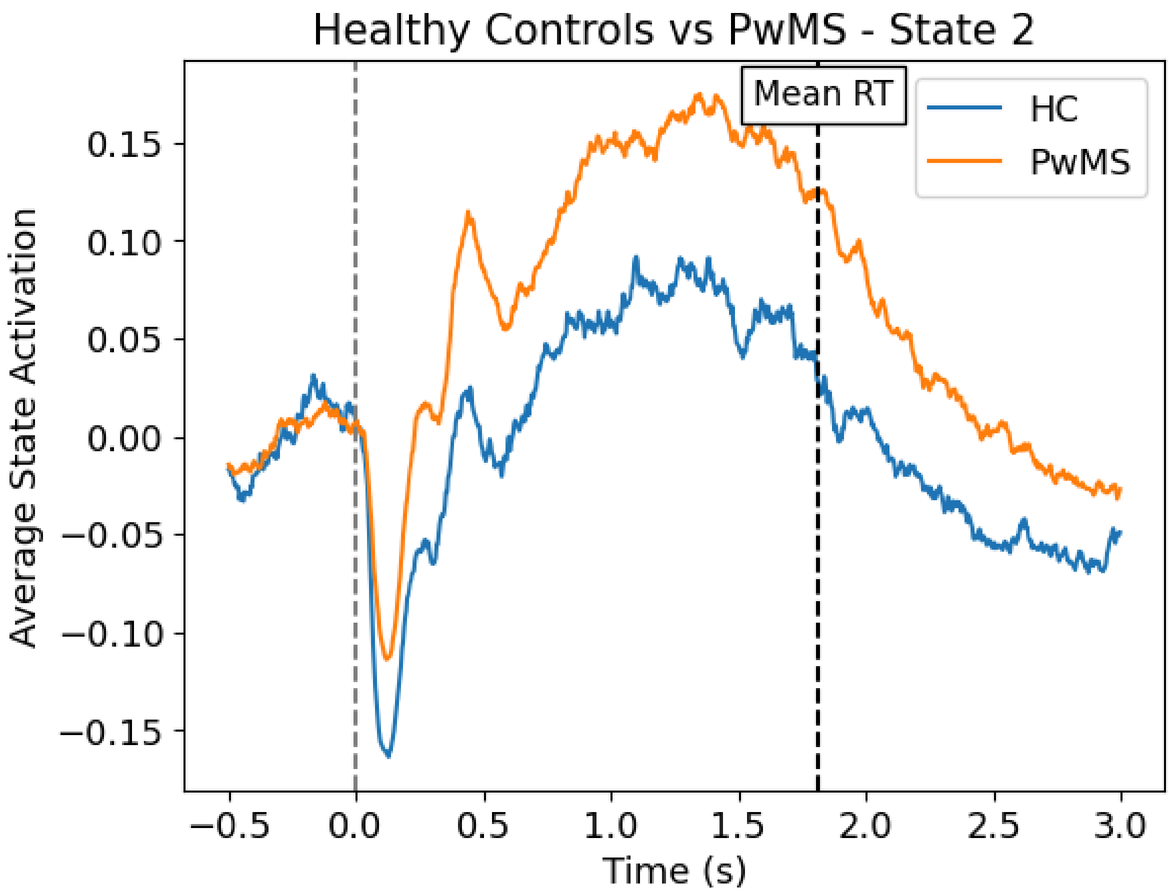
```
/home/olivierb/.local/lib/python3.9/site-packages/glmtools/fit.py:464: Ru
ntimeWarning: invalid value encountered in divide
  copes / denom,
```

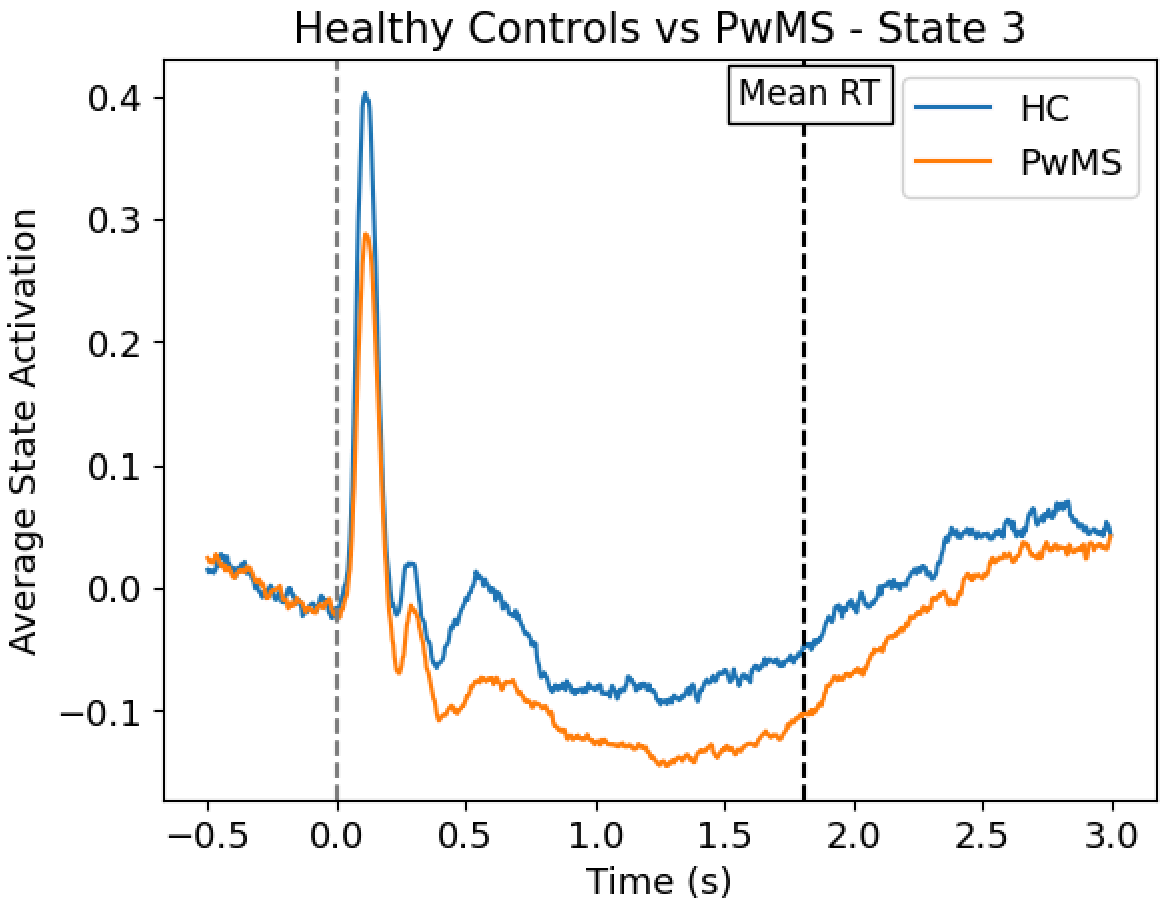
```
Using tstats as metric
Number of significant differences: 36
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(110, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 1000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
```

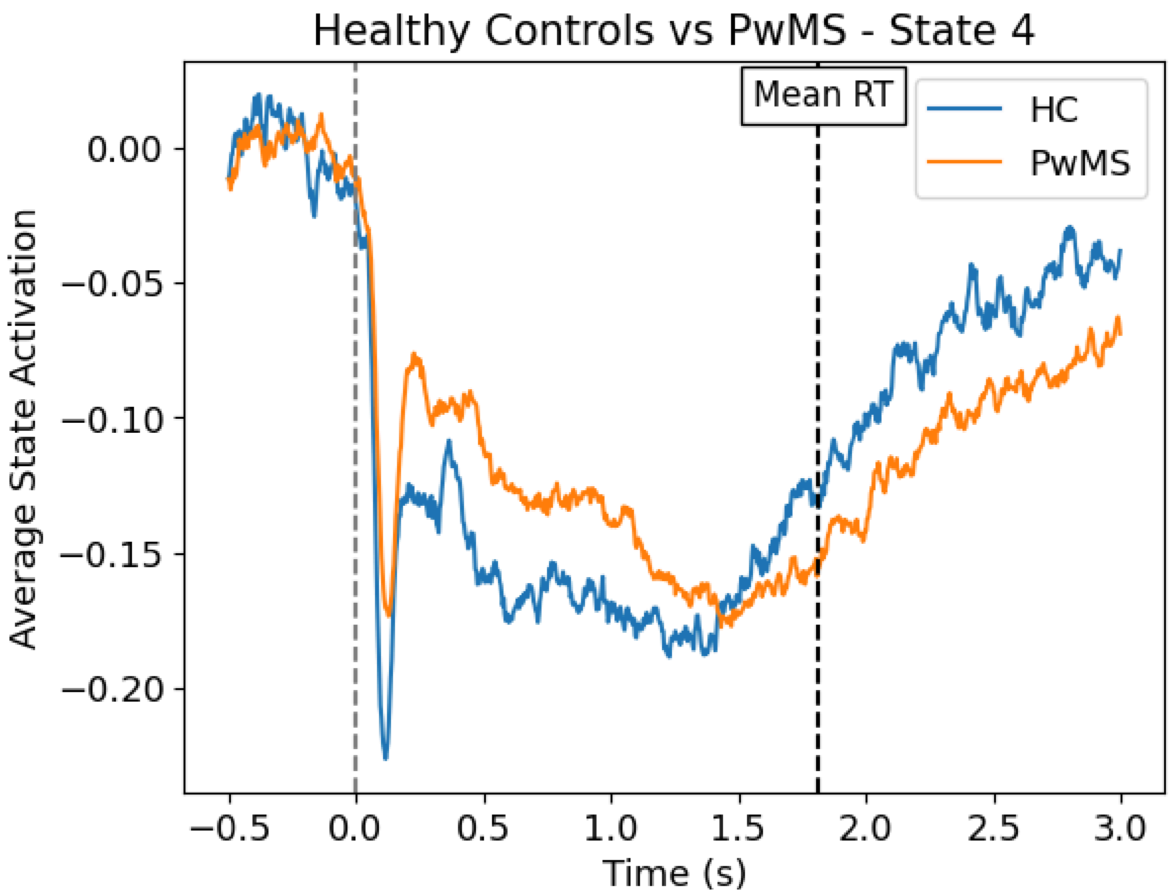
In [89]:

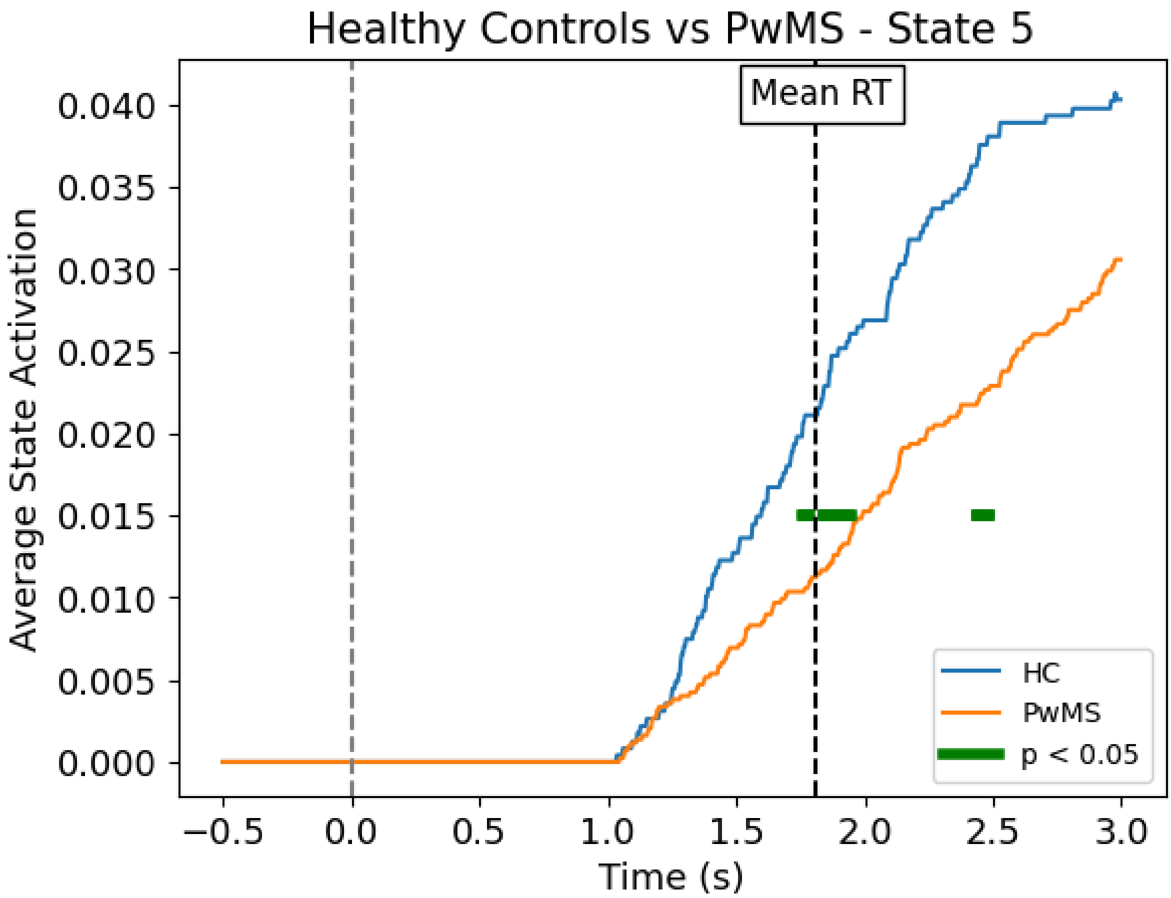
```
from collections import OrderedDict

## Plot MS vs. HC per state and group comparison stat. sign. diff.
for i in range(n_states):
    plt.figure()
    plt.plot(t,np.mean(epochs_incorrect_control,axis=0)[:,i],label='HC')
    plt.plot(t,np.mean(epochs_incorrect_ms,axis=0)[:,i],label='PwMS')
    plt.title(f'Healthy Controls vs PwMS - State {i+1}', fontsize=15)
    plt.axvline(color="gray", linestyle="--")

    plt.xlabel('Time (s)', fontsize=13)
    plt.ylabel('Average State Activation', fontsize=13)
    plt.legend(fontsize=13)
    plt.xticks(fontsize=13)
    plt.yticks(fontsize=13)

    significant = group_diff_pvals[i] < 0.05
    sig_times = t[significant]
    draw = min(np.min(np.mean(epochs_incorrect_control,axis=0)[:,i]), np.mir
    if len(sig_times) > 0:
        dt = t[1] - t[0]
        y = -0.025 + i * 0.01 + draw                # this value needs to b
        for st in sig_times:
            plt.plot((st - dt, st + dt), (y, y), linewidth=4, color='g', lab

        # StackOverflow fix to remove duplicate labels (due to ex. a for loo
        handles, labels = plt.gca().get_legend_handles_labels()
        by_label = OrderedDict(zip(labels, handles))
        plt.legend(by_label.values(), by_label.keys())

    plt.axvline(x=1.81, color="k", linestyle="--")   # 1,668 is the mean rea
    plt.text(0.58, 0.94, 'Mean RT', fontsize = 12, bbox = dict(facecolor = '
```

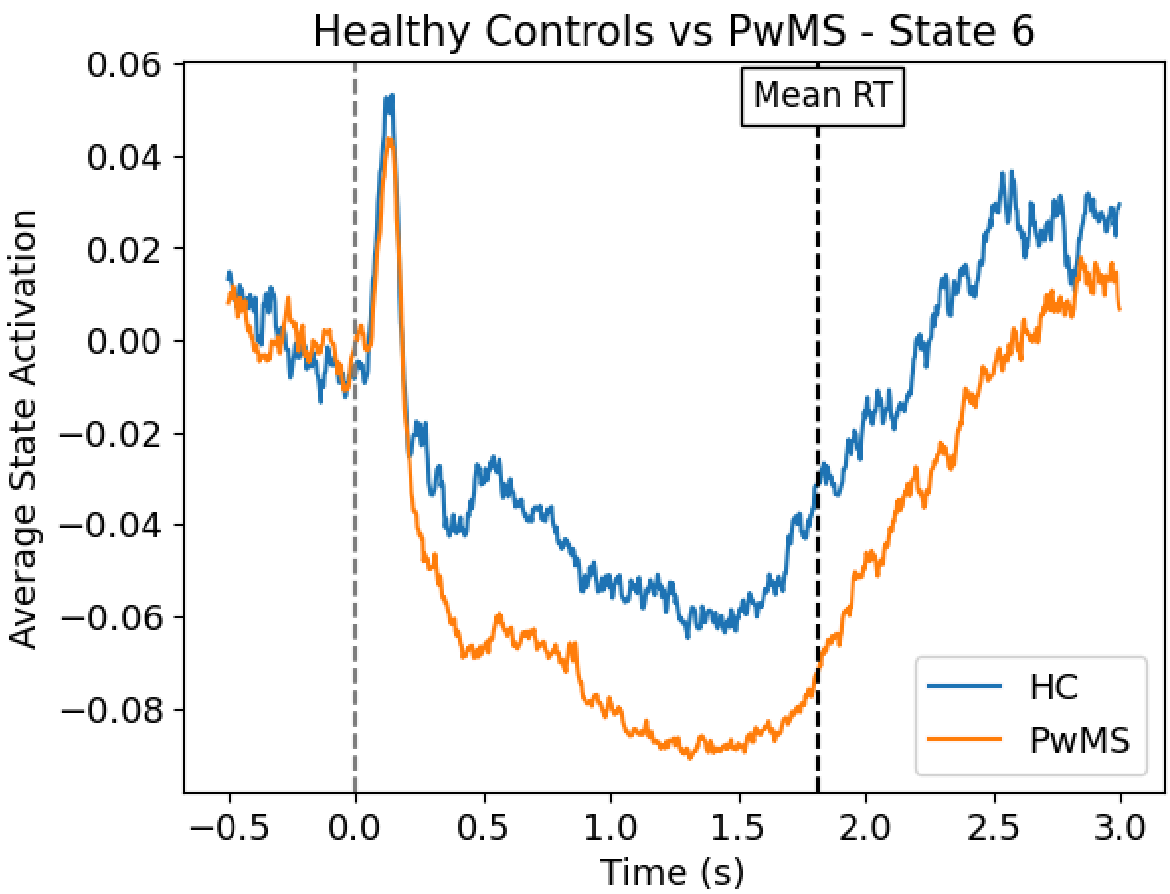

Healthy Controls vs PwMS - State 1
Mean RT
HC
PwMS
Average State Activation
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)

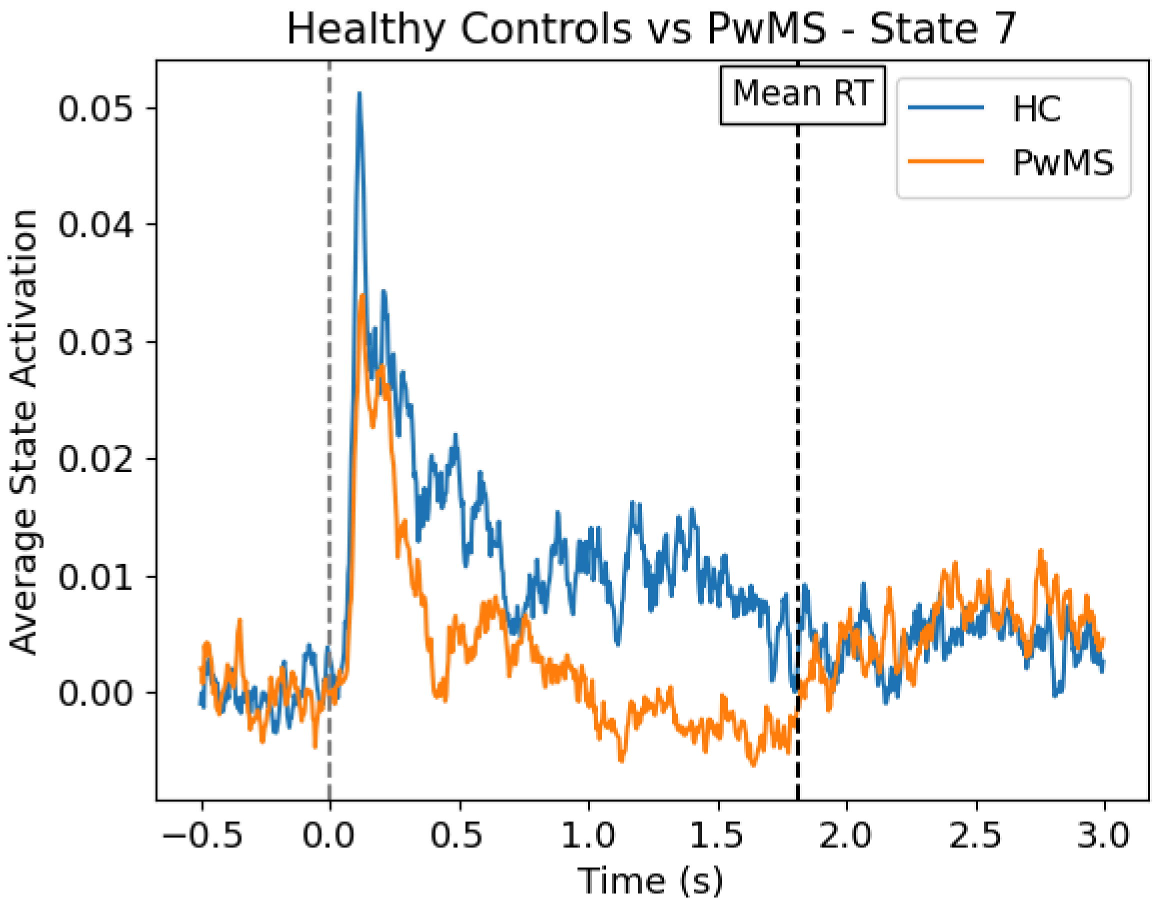

Healthy Controls vs PwMS - State 2
Mean RT
HC
PwMS
Average State Activation
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)

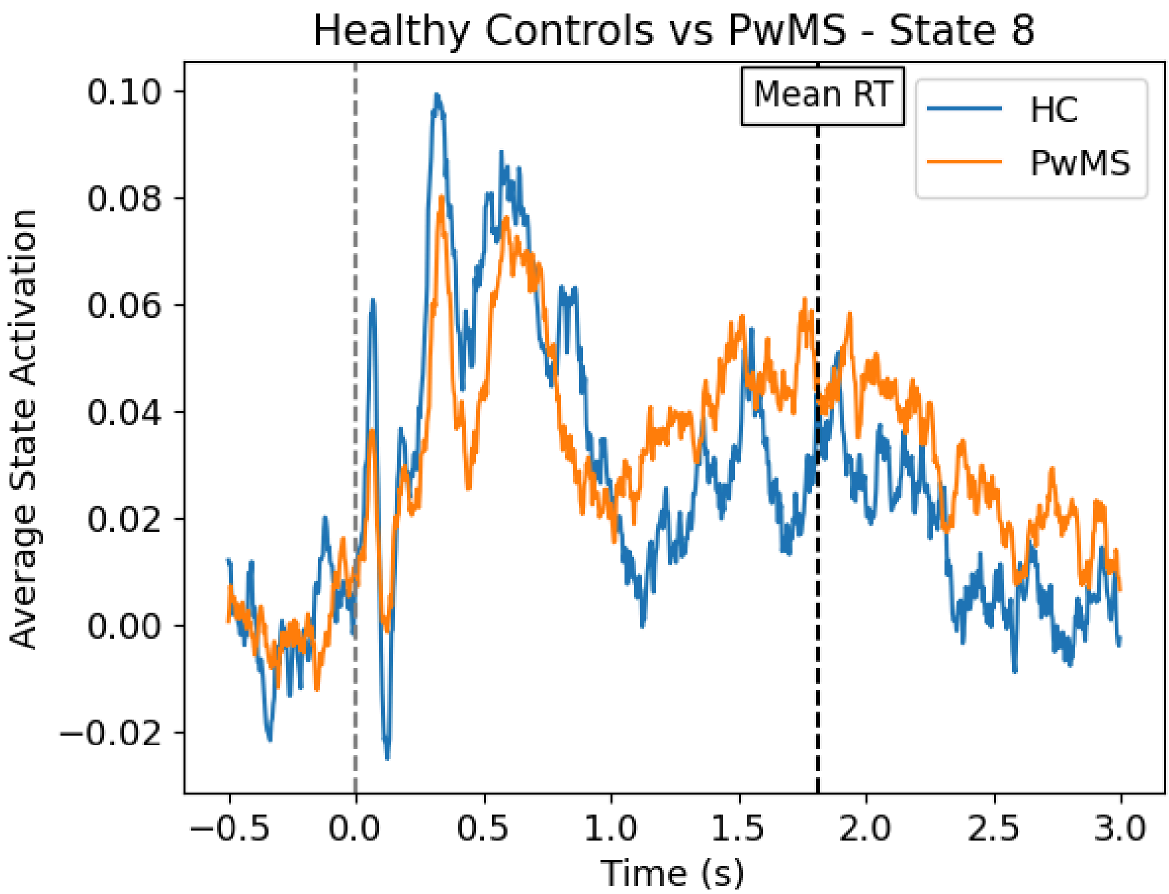

Healthy Controls vs PwMS - State 3
Mean RT
HC
PwMS
Average State Activation
0.4
0.3
0.2
0.1
0.0
−0.1
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Healthy Controls vs PwMS - State 4
Mean RT
HC
PwMS
Average State Activation
0.00
−0.05
−0.10
−0.15
−0.20
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Healthy Controls vs PwMS - State 5
Mean RT
Average State Activation
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)
HC
PwMS
p < 0.05


Healthy Controls vs PwMS - State 6
Mean RT
Average State Activation
0.06
0.04
0.02
0.00
−0.02
−0.04
−0.06
−0.08
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)
HC
PwMS





For CORRECTS vs. INCORRECT trials (all subjects)

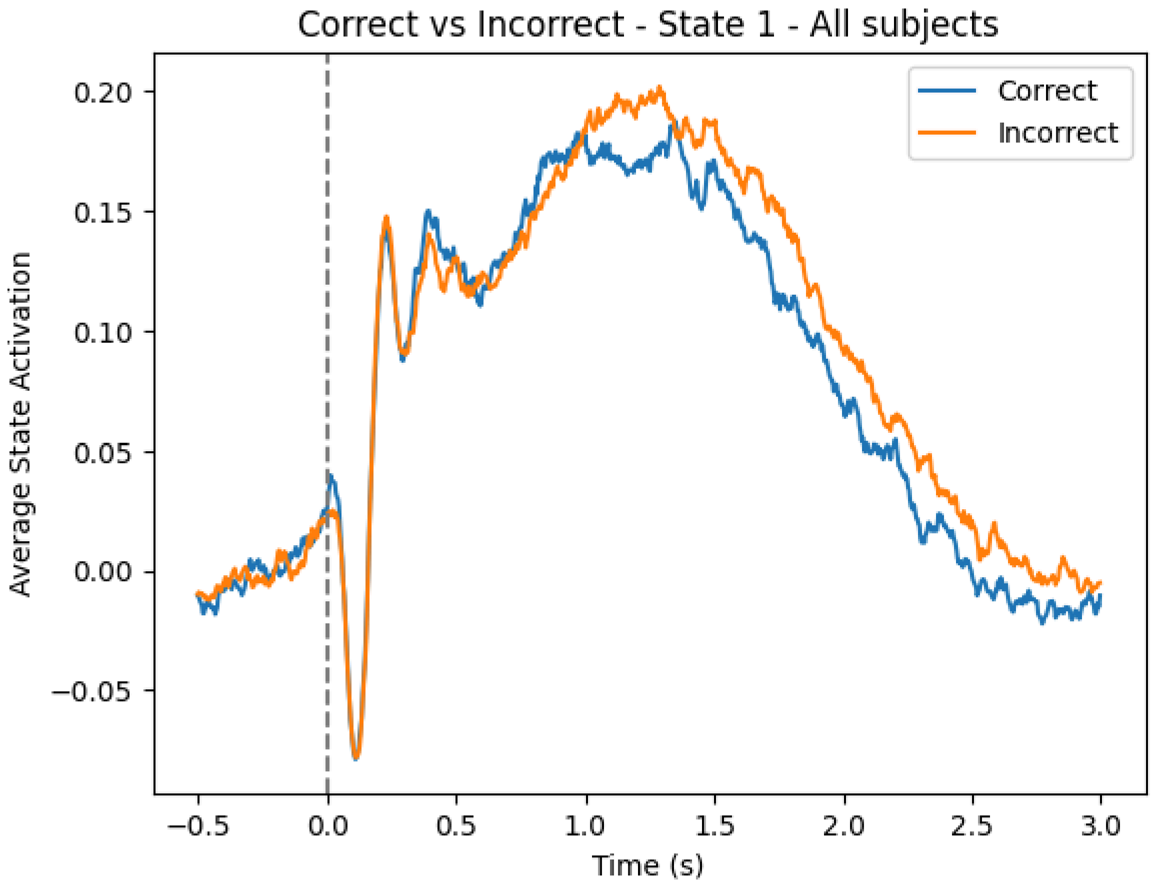
In [90]:
```
# Epoch around events
stc_epochs_correct = []
for s, v in zip(stc, timings_filtered_correct_pad):
    stc_epochs_correct.append(task.epoch(s, v, pre=125, post=750))

stc_epochs_incorrect = []
for s, v in zip(stc, timings_filtered_incorrect_pad):
    stc_epochs_incorrect.append(task.epoch(s, v, pre=125, post=750))

# Concatenate over subjects
concat_stc_epochs_correct = np.concatenate(stc_epochs_correct)
concat_stc_epochs_incorrect = np.concatenate(stc_epochs_incorrect)

# Average over epochs
avg_stc_epoch_correct = np.nanmean(concat_stc_epochs_correct, axis=0)
avg_stc_epoch_incorrect = np.nanmean(concat_stc_epochs_incorrect, axis=0)

# Baseline correct
base_corr = np.nanmean(avg_stc_epoch_correct[:pre], axis=0, keepdims=True)
base_incorr = np.nanmean(avg_stc_epoch_incorrect[:pre], axis=0, keepdims=Tru

# Remove it from the epoched state time courses
avg_stc_epoch_correct = avg_stc_epoch_correct - base_corr
avg_stc_epoch_incorrect = avg_stc_epoch_incorrect - base_incorr
```

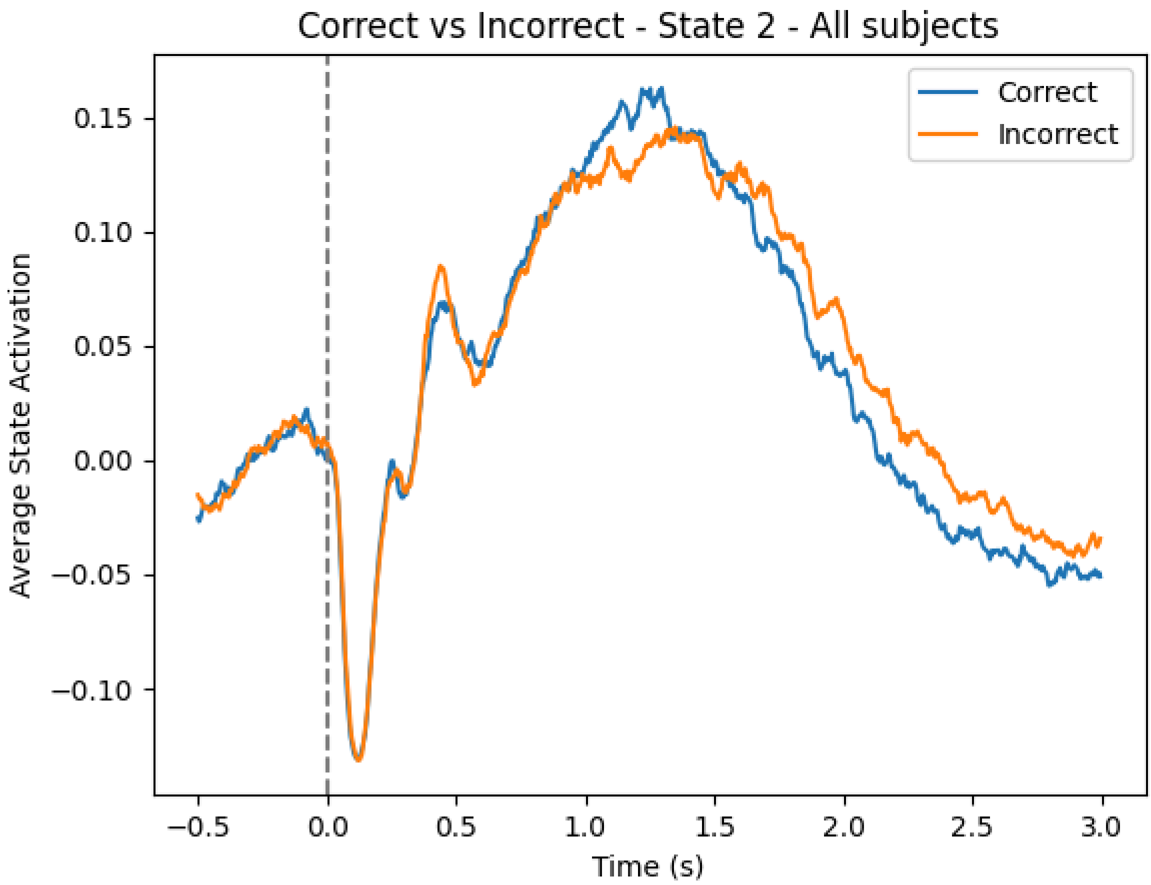
In [91]:
```
print(np.shape(avg_stc_epoch_correct))
print(np.shape(avg_stc_epoch_incorrect))
```

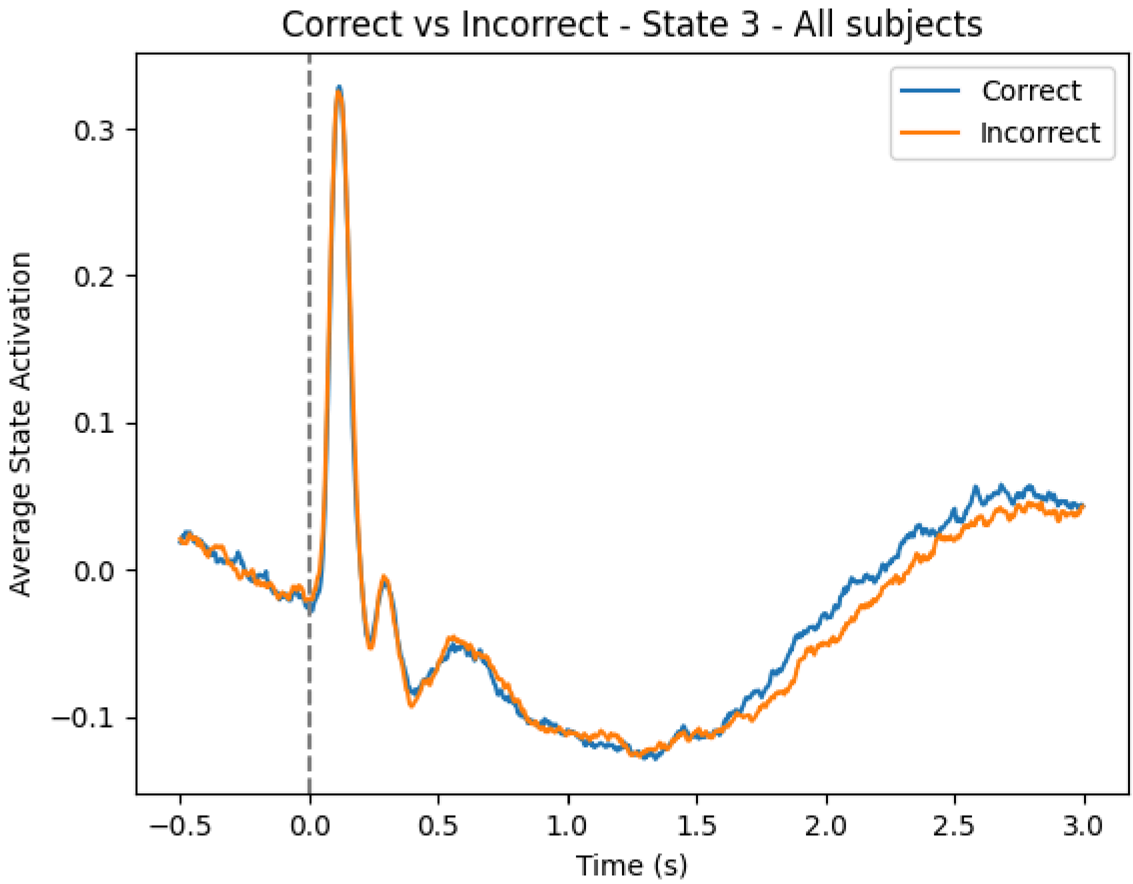
```
(875, 8)
(875, 8)
```

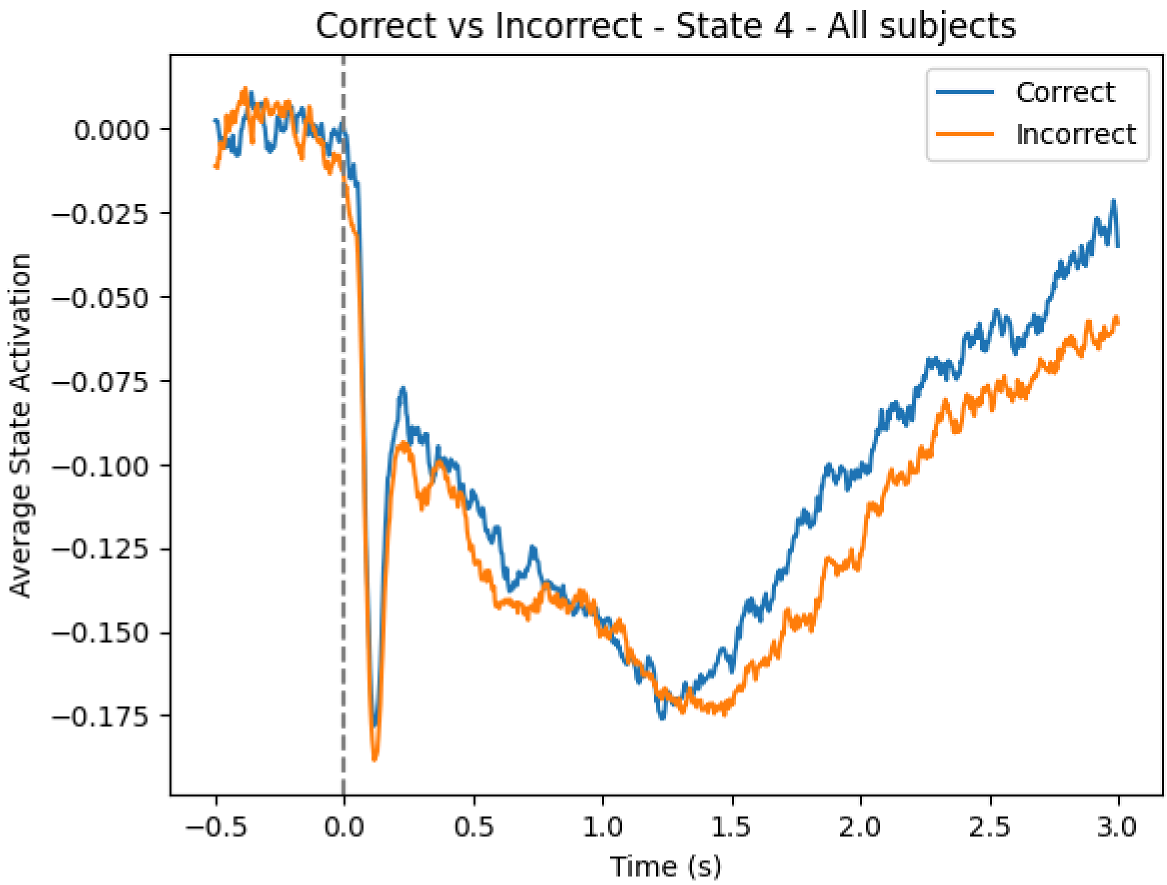
All subjects

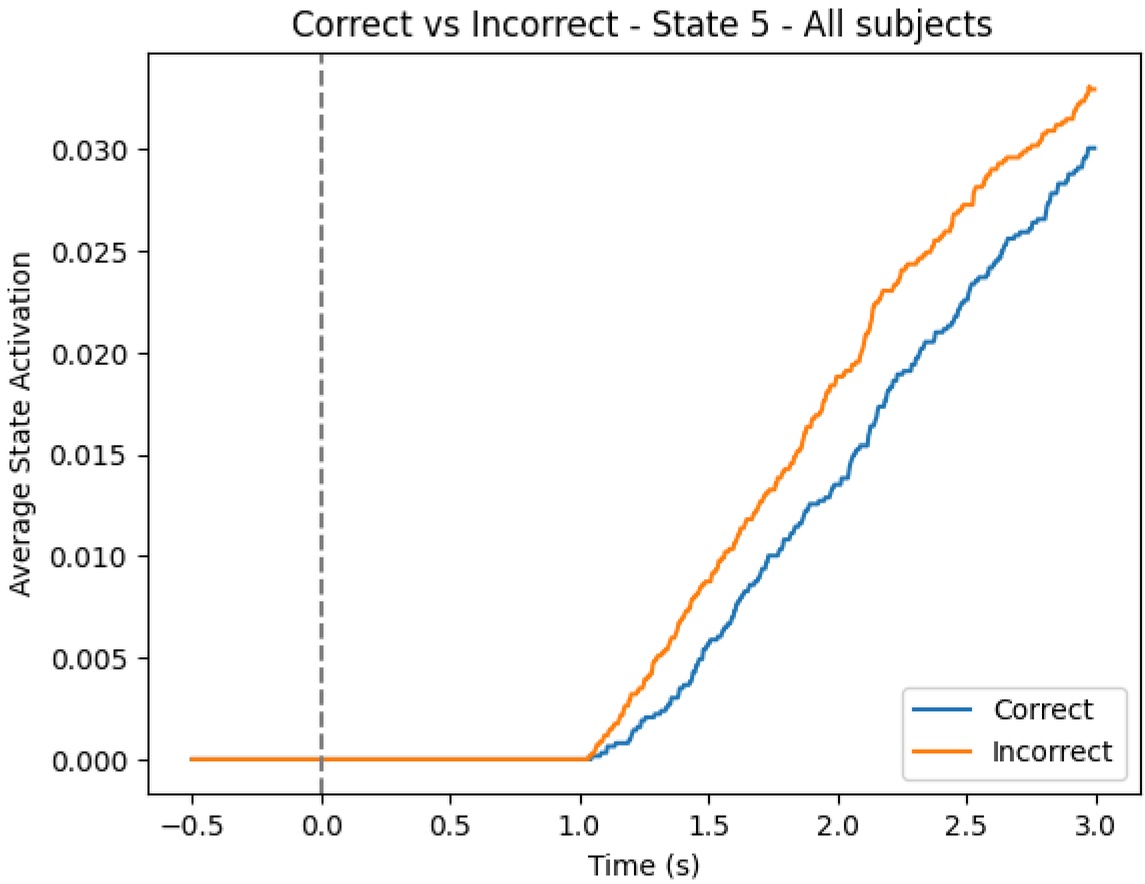
In [92]:
```
fs = 250
n_states = avg_stc_epoch_correct.shape[1]  # number of states
t = (np.arange(avg_stc_epoch_correct.shape[0]) - 250/2) / fs  # time axis

## Plot Correct vs. Incorrect per state (over all subjects)
for i in range(n_states):
    plt.figure()
    plt.plot(t,avg_stc_epoch_correct[:,i],label='Correct')
    plt.plot(t,avg_stc_epoch_incorrect[:,i],label='Incorrect')
    plt.title(f'Correct vs Incorrect - State {i+1} - All subjects')
    plt.legend()
    plt.axvline(color="gray", linestyle="--")
    plt.xlabel('Time (s)')
    plt.ylabel('Average State Activation')
```

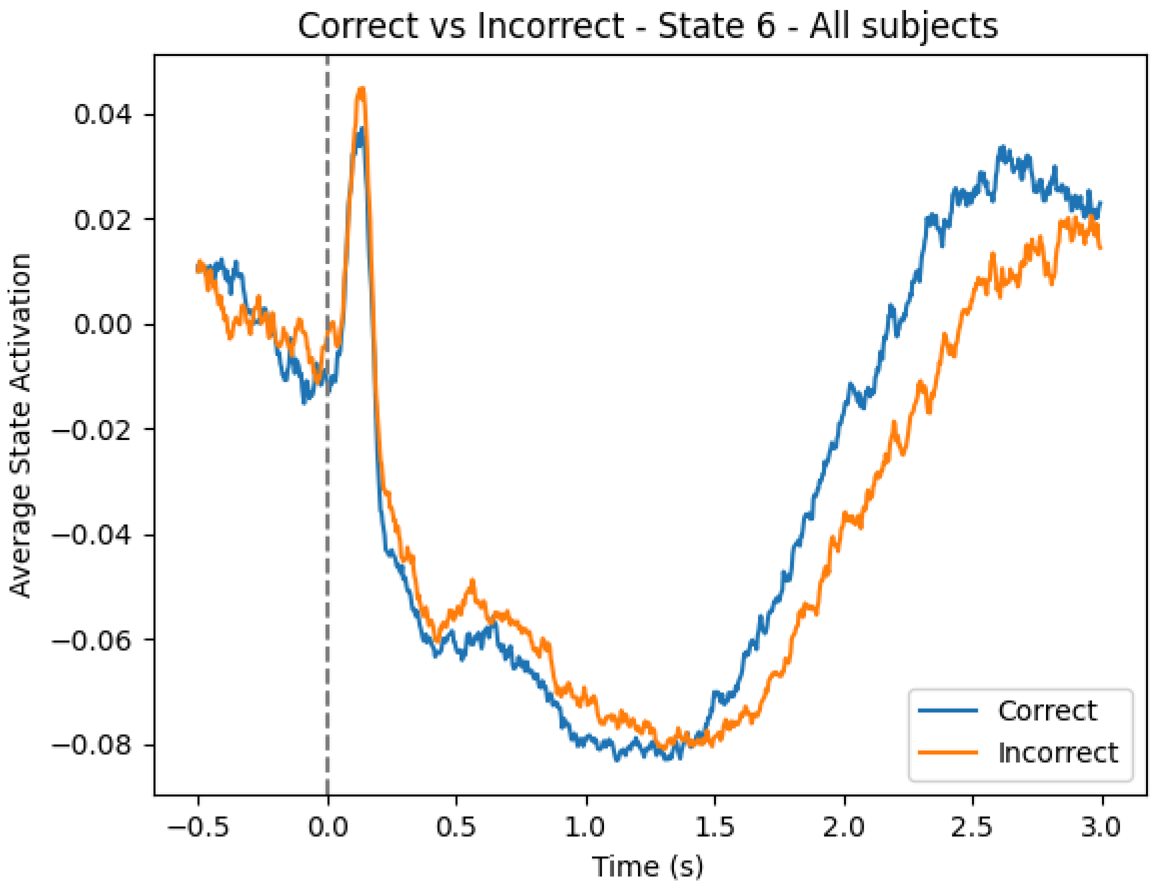

Correct vs Incorrect - State 1 - All subjects
Correct
Incorrect
Average State Activation
0.20
0.15
0.10
0.05
0.00
−0.05
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)

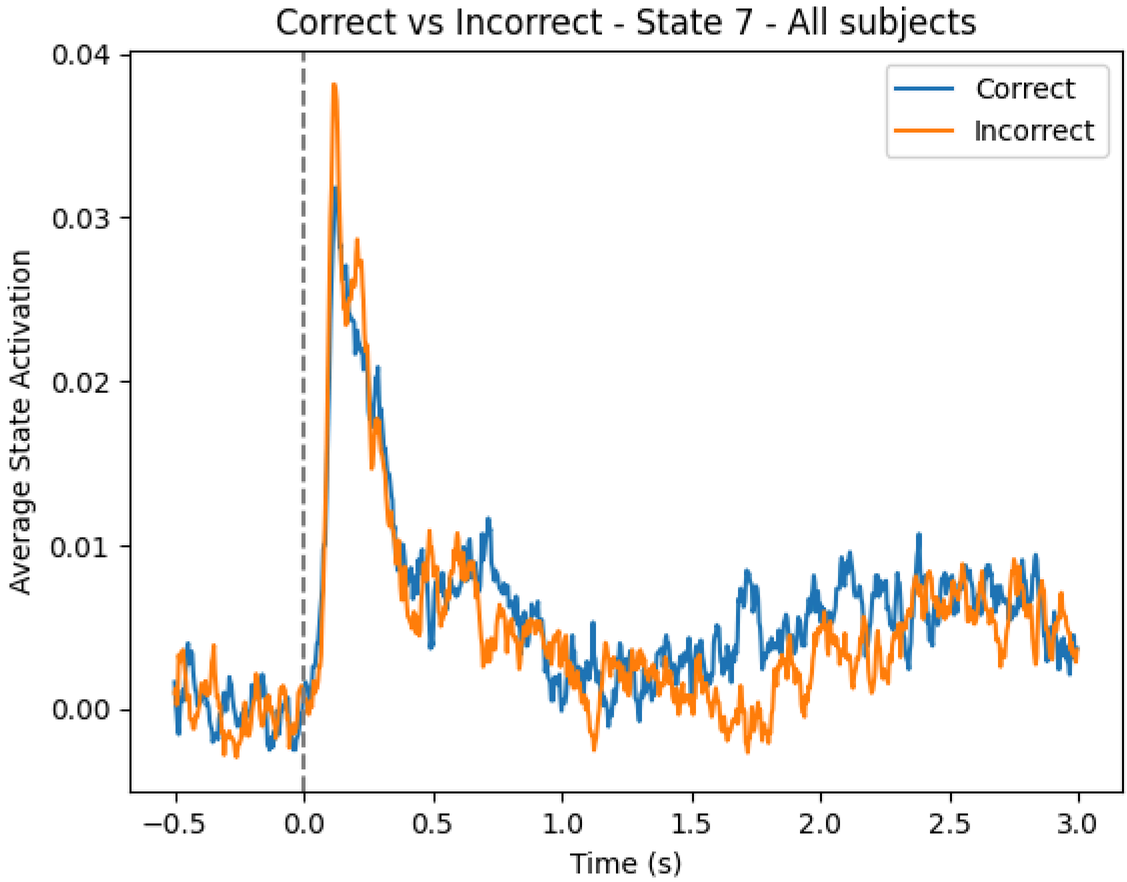

Correct vs Incorrect - State 2 - All subjects
Correct
Incorrect
Average State Activation
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)

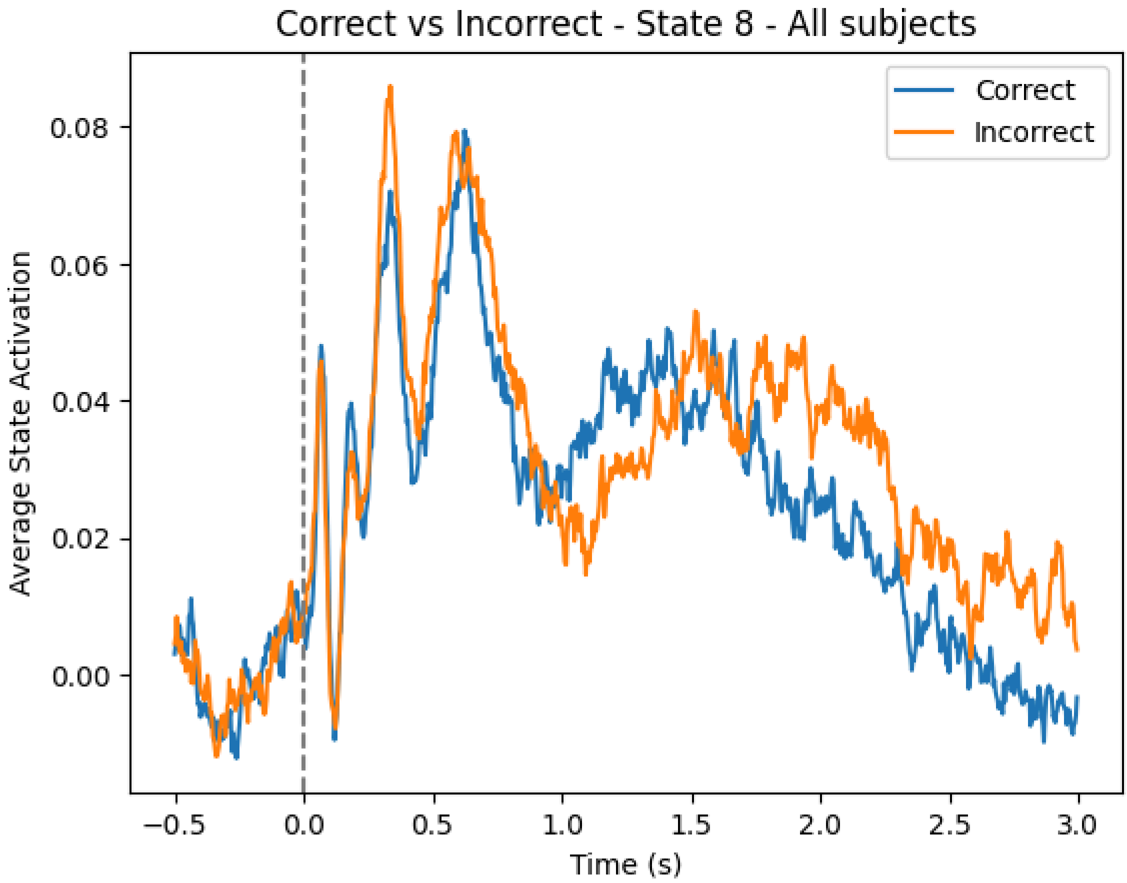

Correct vs Incorrect - State 3 - All subjects
Correct
Incorrect
Average State Activation
0.3
0.2
0.1
0.0
−0.1
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Correct vs Incorrect - State 4 - All subjects
Correct
Incorrect
Average State Activation
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
−0.150
−0.175
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Correct vs Incorrect - State 5 - All subjects
Average State Activation
0.030
0.025
0.020
0.015
0.010
0.005
0.000
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)
Correct
Incorrect


Correct vs Incorrect - State 6 - All subjects
Average State Activation
0.04
0.02
0.00
−0.02
−0.04
−0.06
−0.08
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)
Correct
Incorrect





In [93]:
```
## Get lists for subject-averages of the data, i.e. average correct and avei
print(np.shape(concat_stc_epochs_correct))

from osl_dynamics.analysis import statistics

# We already have the trial specific epochs separated by subjects in stc_epo
# we just need to average each subject's trials separately
```

```
subj_stc_epochs_correct = []
subj_stc_epochs_incorrect = []

for epochs in stc_epochs_correct:
    subj_stc_epochs_correct.append(np.nanmean(epochs, axis=0))
subj_stc_epochs_correct = np.array(subj_stc_epochs_correct)
print(subj_stc_epochs_correct.shape)

for epochs in stc_epochs_incorrect:
    subj_stc_epochs_incorrect.append(np.nanmean(epochs, axis=0))
subj_stc_epochs_incorrect = np.array(subj_stc_epochs_incorrect)
print(subj_stc_epochs_incorrect.shape)

# Baseline correct using the samples before the event
pre = 125  # number of samples before the event
subj_stc_epochs_correct -= np.mean(subj_stc_epochs_correct[:, :pre], axis=1,
subj_stc_epochs_incorrect -= np.mean(subj_stc_epochs_incorrect[:, :pre], axi

## Need to make 1 single data_test array which has 110 x 2 elements [1, 1, 1
concatenated_epochs_corr_incorr = np.concatenate((subj_stc_epochs_correct, s
print(np.shape(concatenated_epochs_corr_incorr))

assignments_all = []
for i in range(len(concatenated_epochs_corr_incorr)):
    if i < int(len(concatenated_epochs_corr_incorr)/2):
        assignments_all.append(1)
    else:
        assignments_all.append(2)
```

```
(6287, 875, 8)
(110, 875, 8)
(110, 875, 8)
(220, 875, 8)
```

In [94]:

```
## Max stat permutation testing for statistically significant differences
stimulus_type_diff_pvals = []
for i in range(n_states):
    data_test = concatenated_epochs_corr_incorr[:,:,i]
    print(np.shape(data_test))

    # Do stats testing
    diff, pvalues = statistics.group_diff_max_stat_perm(
        data_test,
        assignments_all,
        n_perm=5000,
    )
    stimulus_type_diff_pvals.append(pvalues)
    print("Number of significant differences:", np.sum(pvalues < 0.05))
```

```
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 2
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
```

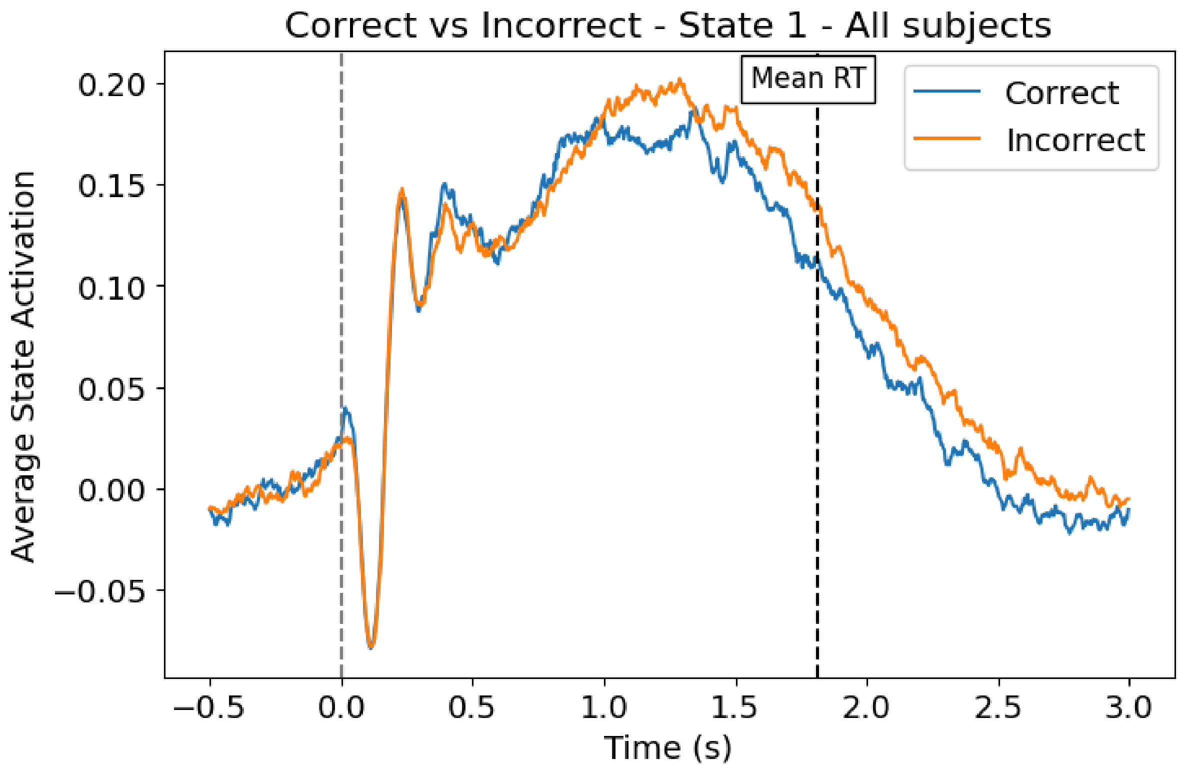
```
/home/olivierb/.local/lib/python3.9/site-packages/glmtools/fit.py:464: Ru
ntimeWarning: invalid value encountered in divide
  copes / denom,
```

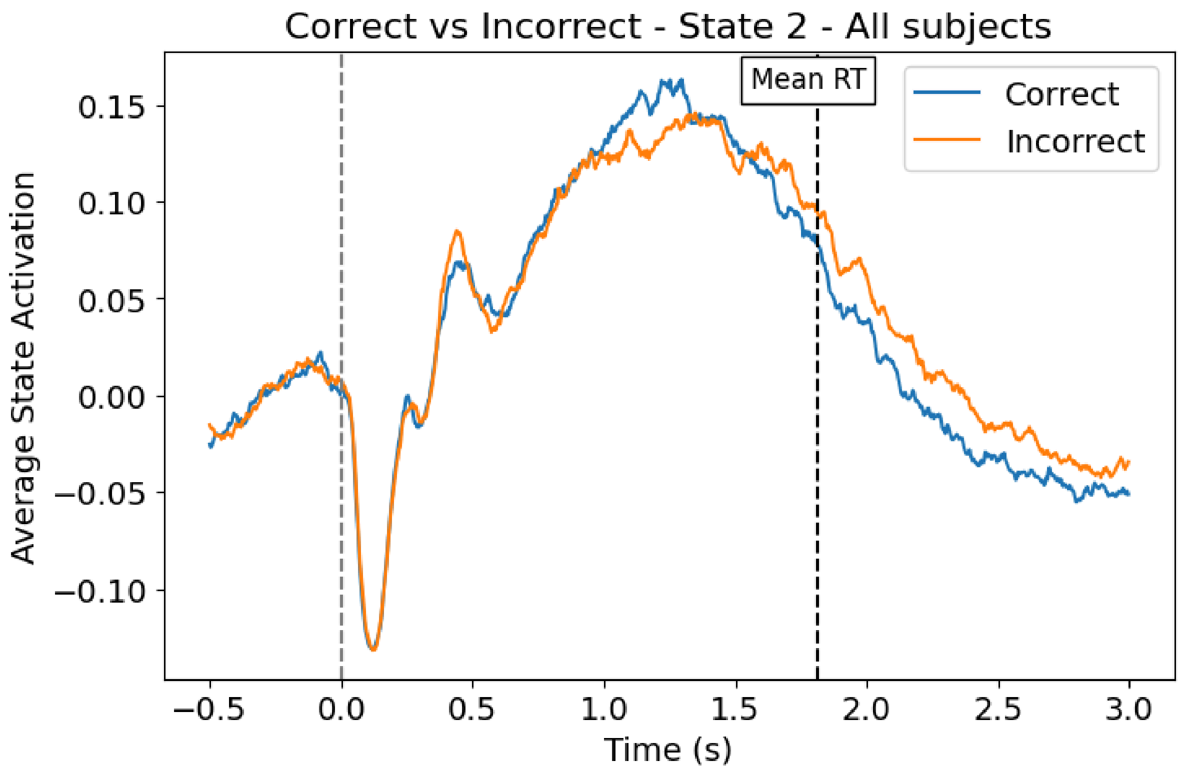
```
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
```

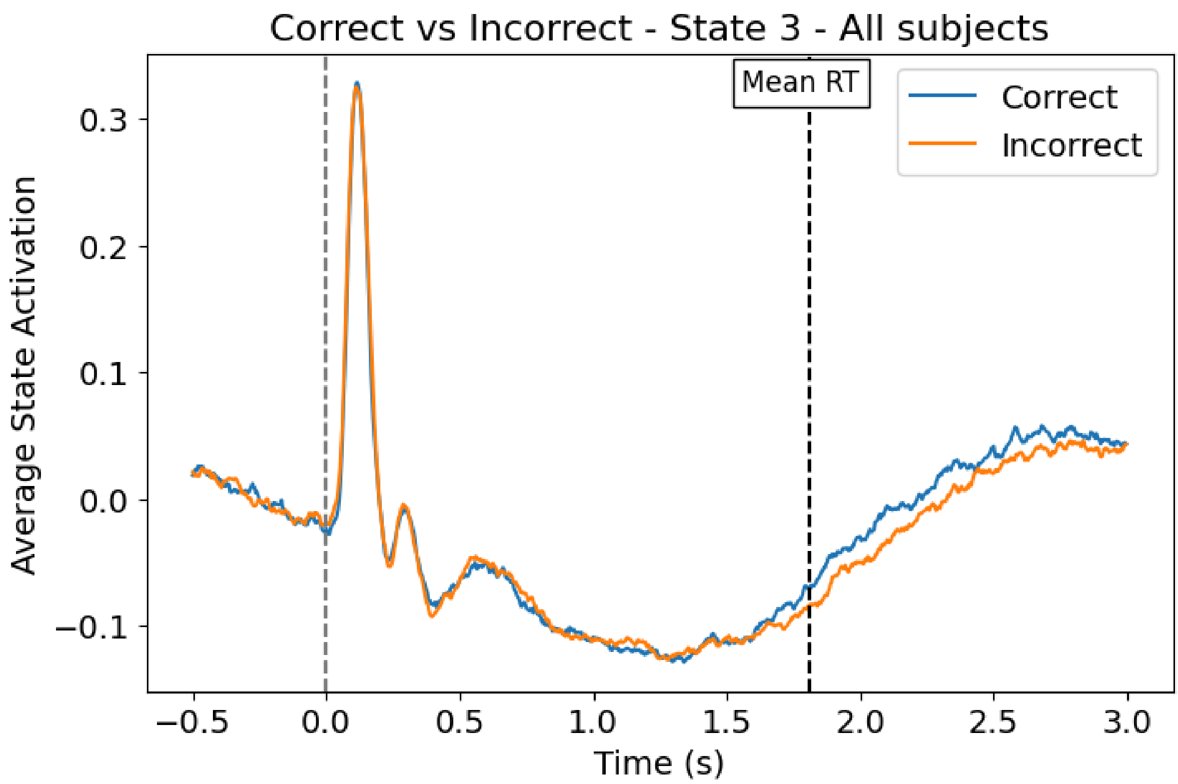
In [95]:

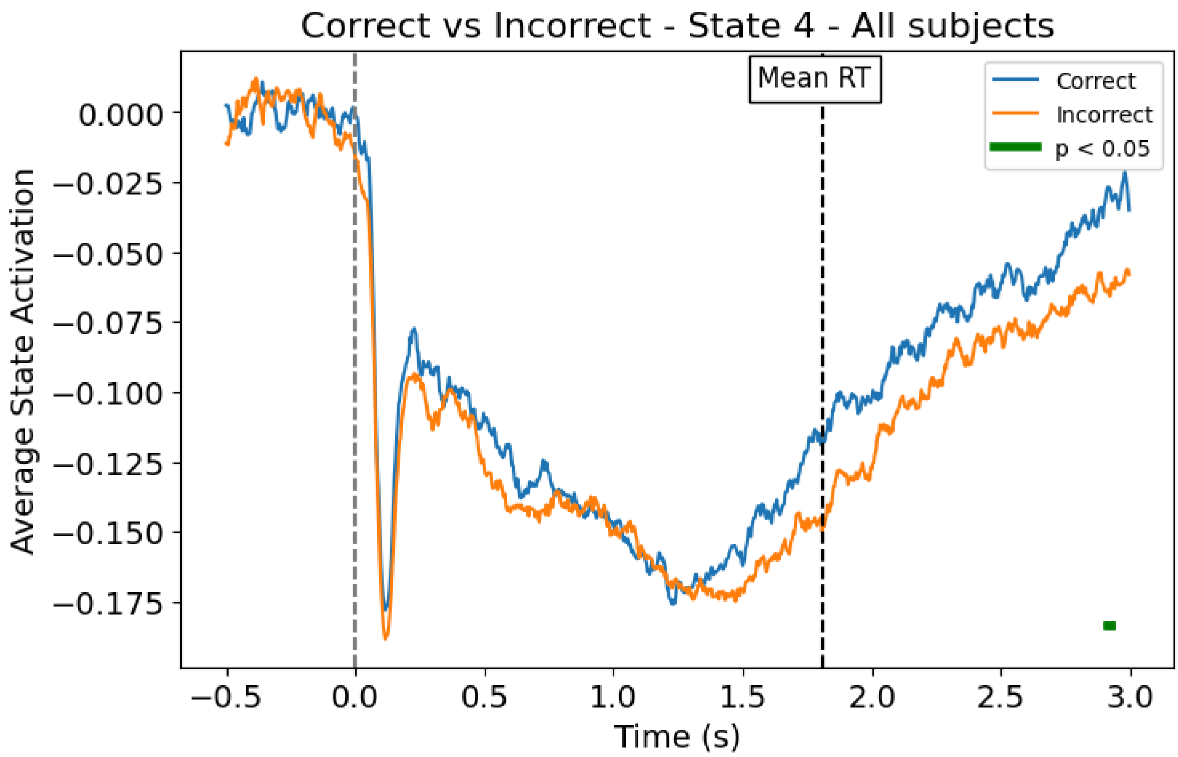
```
from collections import OrderedDict

## Plot RRMS vs. HC per state and group comparison stat. sign. diff.
for i in range(n_states):
```

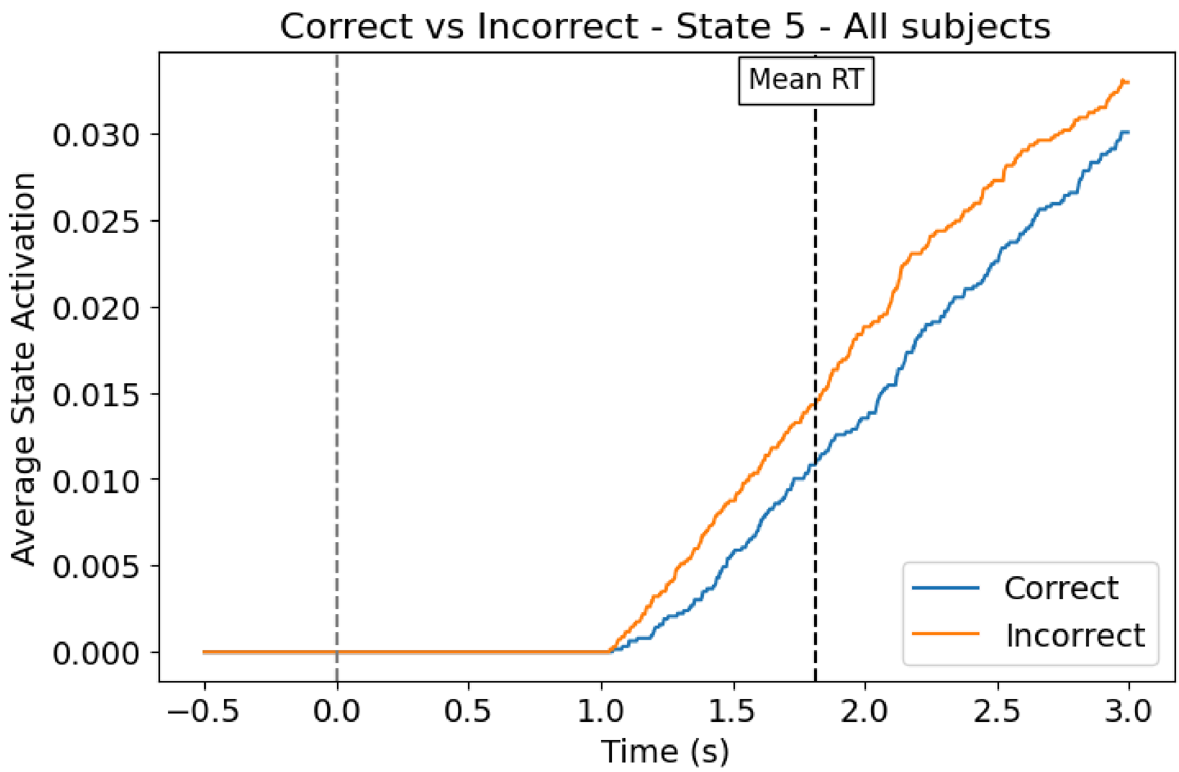
```
    plt.figure(figsize=(8,5))
    plt.plot(t,avg_stc_epoch_correct[:,i],label='Correct')
    plt.plot(t,avg_stc_epoch_incorrect[:,i],label='Incorrect')
    plt.title(f'Correct vs Incorrect - State {i+1} - All subjects', fontsize
    plt.axvline(color="gray", linestyle="--")

    plt.axvline(color="gray", linestyle="--")

    plt.xlabel('Time (s)', fontsize=14)
    plt.ylabel('Average State Activation', fontsize=14)
    plt.legend(fontsize=14)
    plt.xticks(fontsize=14)
    plt.yticks(fontsize=14)

    plt.axvline(x=1.81, color="k", linestyle="--")   # 1,668 is the mean rea
    plt.text(0.58, 0.94, 'Mean RT', fontsize = 12, bbox = dict(facecolor = '

    significant = stimulus_type_diff_pvals[i] < 0.05
    sig_times = t[significant]
    draw = min(np.min(avg_stc_epoch_correct[:,i]), np.min(avg_stc_epoch_inco
    if len(sig_times) > 0:
        dt = t[1] - t[0]
        y = -0.025 + i * 0.01 + draw                # this value needs to b
        for st in sig_times:
            plt.plot((st - dt, st + dt), (y, y), linewidth=4, color='g', lab

        # StackOverflow fix to remove duplicate labels (due to ex. a for loo
        handles, labels = plt.gca().get_legend_handles_labels()
        by_label = OrderedDict(zip(labels, handles))
        plt.legend(by_label.values(), by_label.keys())
```

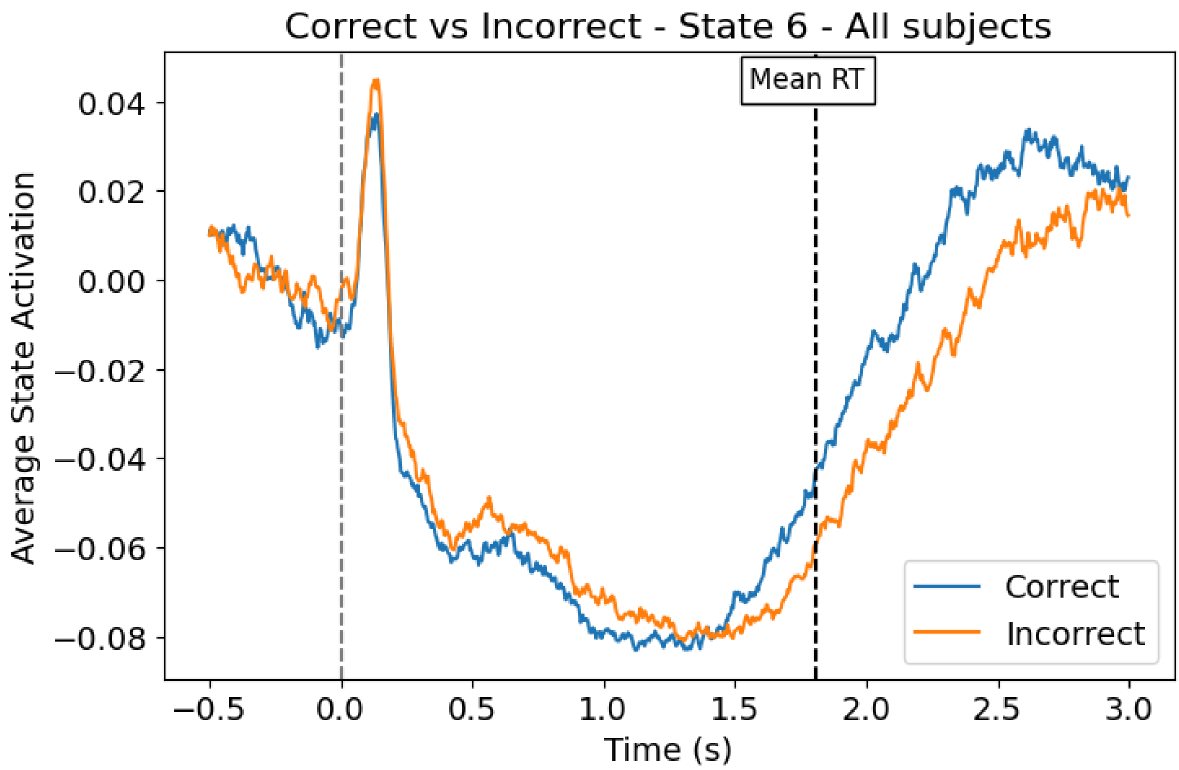


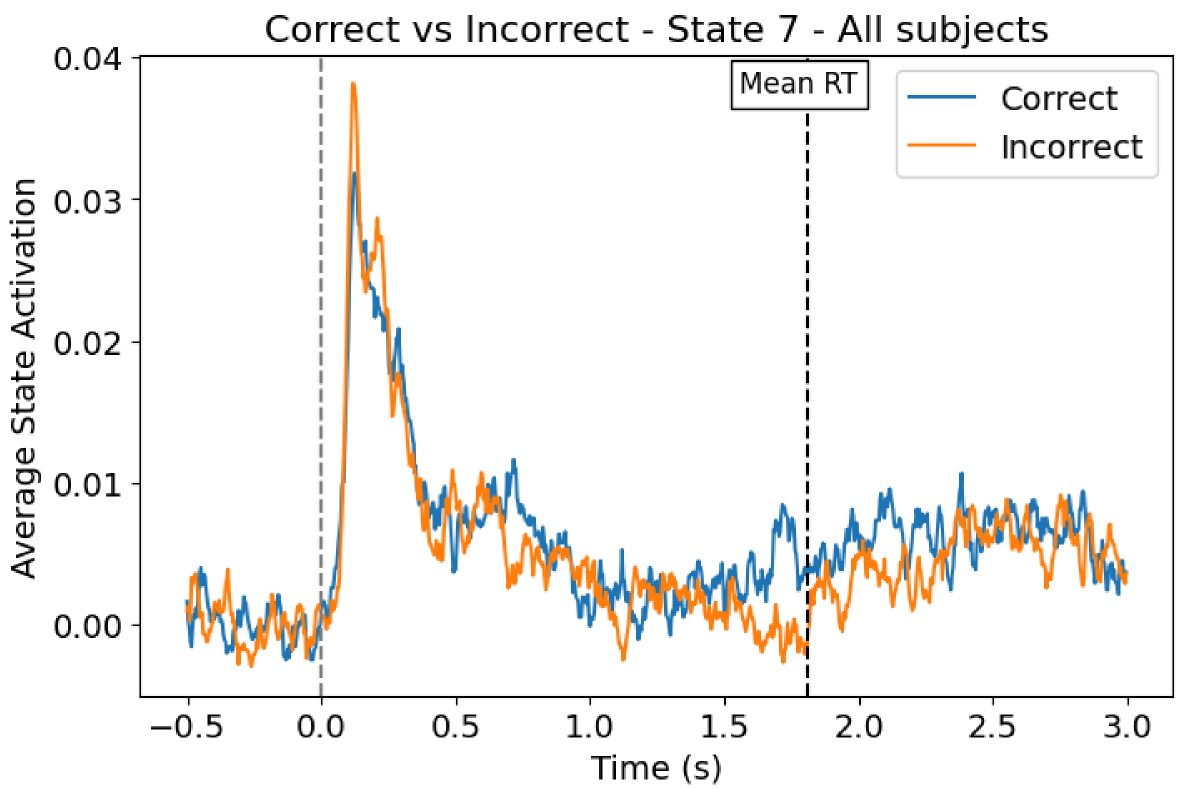

Correct vs Incorrect - State 2 - All subjects
Mean RT
Correct
Incorrect
Average State Activation
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)

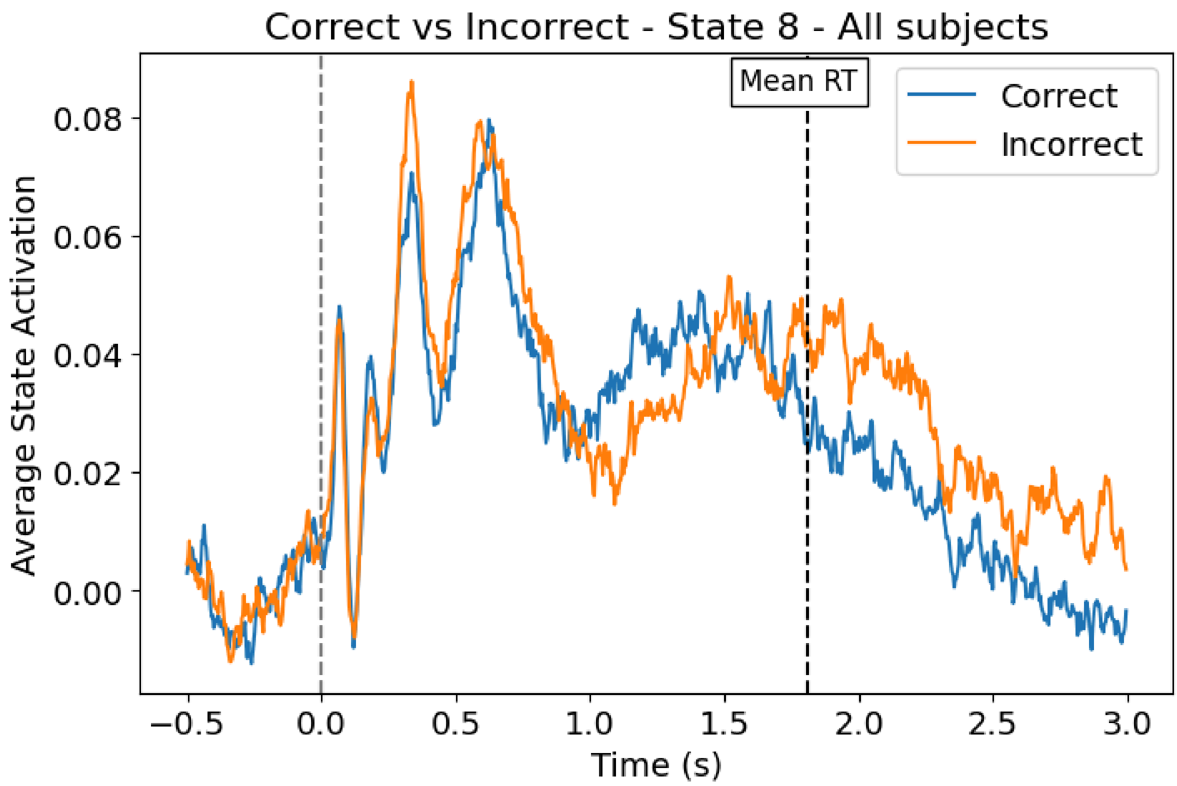

Correct vs Incorrect - State 3 - All subjects
Mean RT
Correct
Incorrect
Average State Activation
0.3
0.2
0.1
0.0
−0.1
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Correct vs Incorrect - State 4 - All subjects
Mean RT
Correct
Incorrect
p < 0.05
Average State Activation
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
−0.150
−0.175
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Correct vs Incorrect - State 5 - All subjects
Mean RT
Correct
Incorrect
Average State Activation
0.030
0.025
0.020
0.015
0.010
0.005
0.000
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Correct vs Incorrect - State 6 - All subjects
Mean RT
Correct
Incorrect
Average State Activation
0.04
0.02
0.00
−0.02
−0.04
−0.06
−0.08
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Correct vs Incorrect - State 7 - All subjects
Mean RT
Correct
Incorrect
Average State Activation
0.04
0.03
0.02
0.01
0.00
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)



Only HC

In [96]:

```
assignments_HC = []
for i in range(len(concatenated_epochs_corr_incorr)):
    if i < int(len(concatenated_epochs_corr_incorr)/2):
        if i in df_control_idx:
            assignments_HC.append(1)
        else:
            assignments_HC.append(0)
    else:
        if i in np.array(df_control_idx) + int(len(concatenated_epochs_corr_
            assignments_HC.append(2)
        else:
            assignments_HC.append(0)
```

In [97]:

```
## Max stat permutation testing for statistically significant differences
stimulus_type_diff_pvals_HC = []
for i in range(n_states):
    data_test = concatenated_epochs_corr_incorr[:,:,i]
    print(np.shape(data_test))

    # Do stats testing
    diff, pvalues = statistics.group_diff_max_stat_perm(
        data_test,
        assignments_HC,
        n_perm=5000,
    )
    stimulus_type_diff_pvals_HC.append(pvalues)
    print("Number of significant differences:", np.sum(pvalues < 0.05))
```

```
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
```

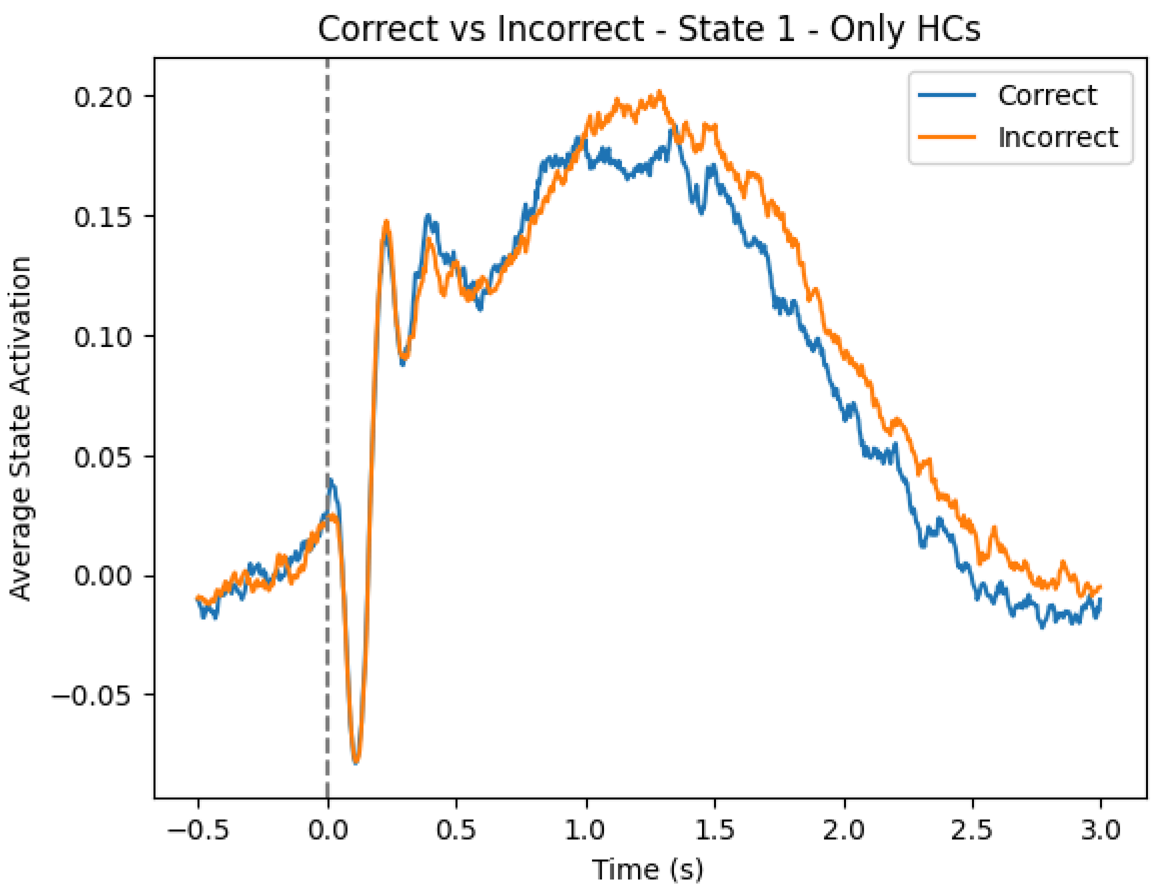
```
/home/olivierb/.local/lib/python3.9/site-packages/glmtools/fit.py:464: Ru
ntimeWarning: invalid value encountered in divide
  copes / denom,
```

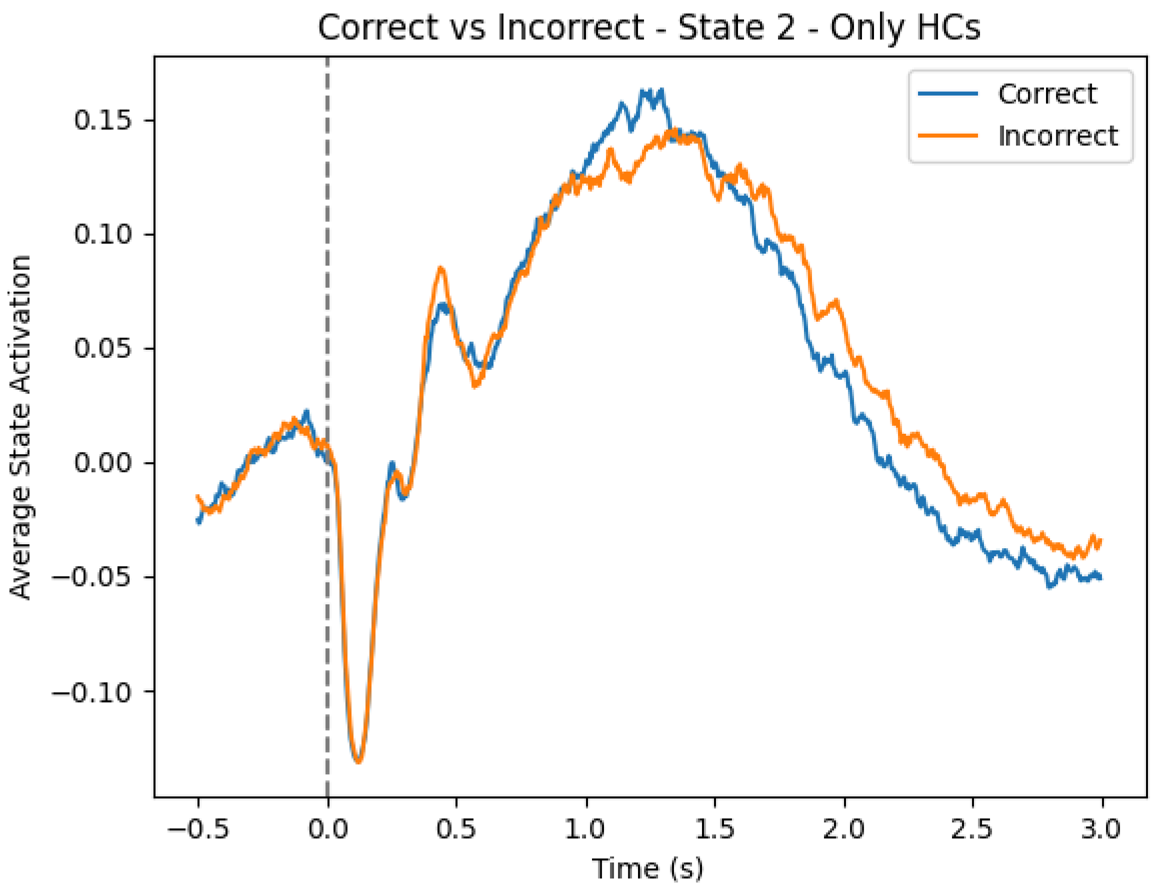
```
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
```

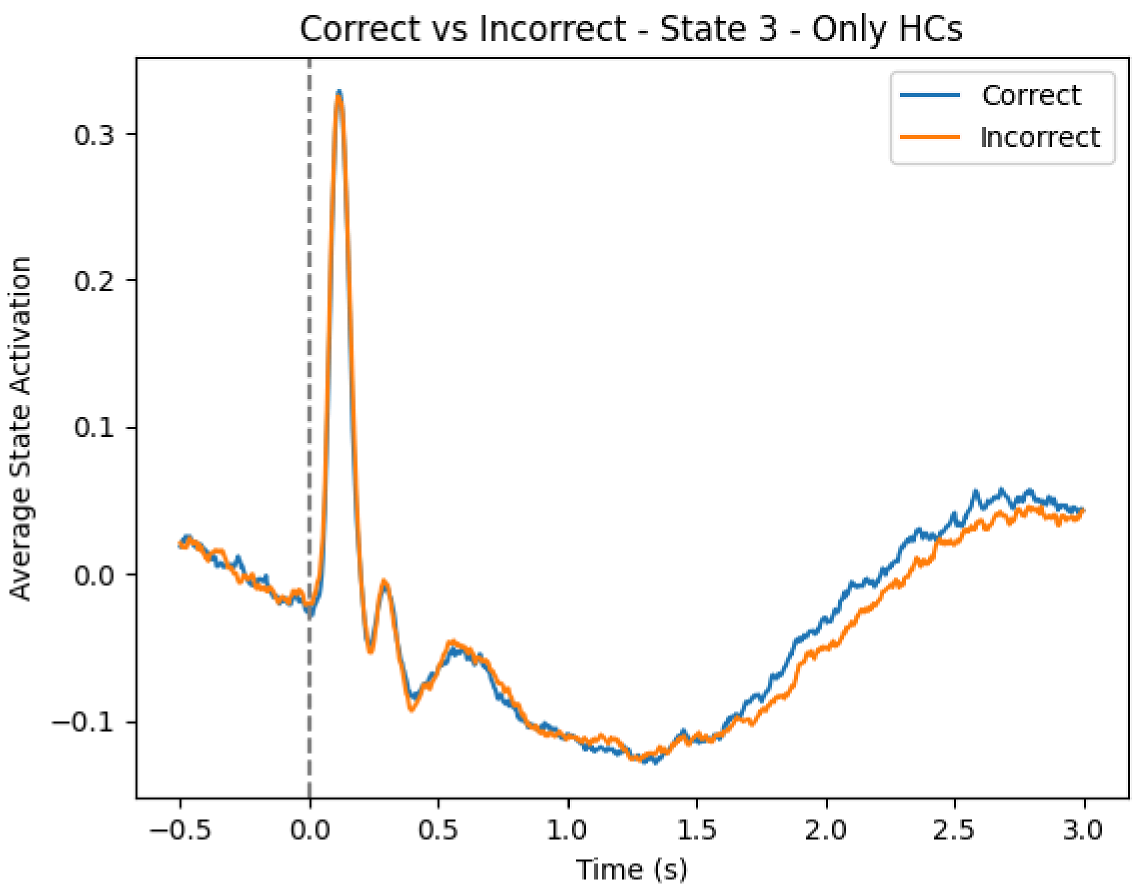
In [98]:

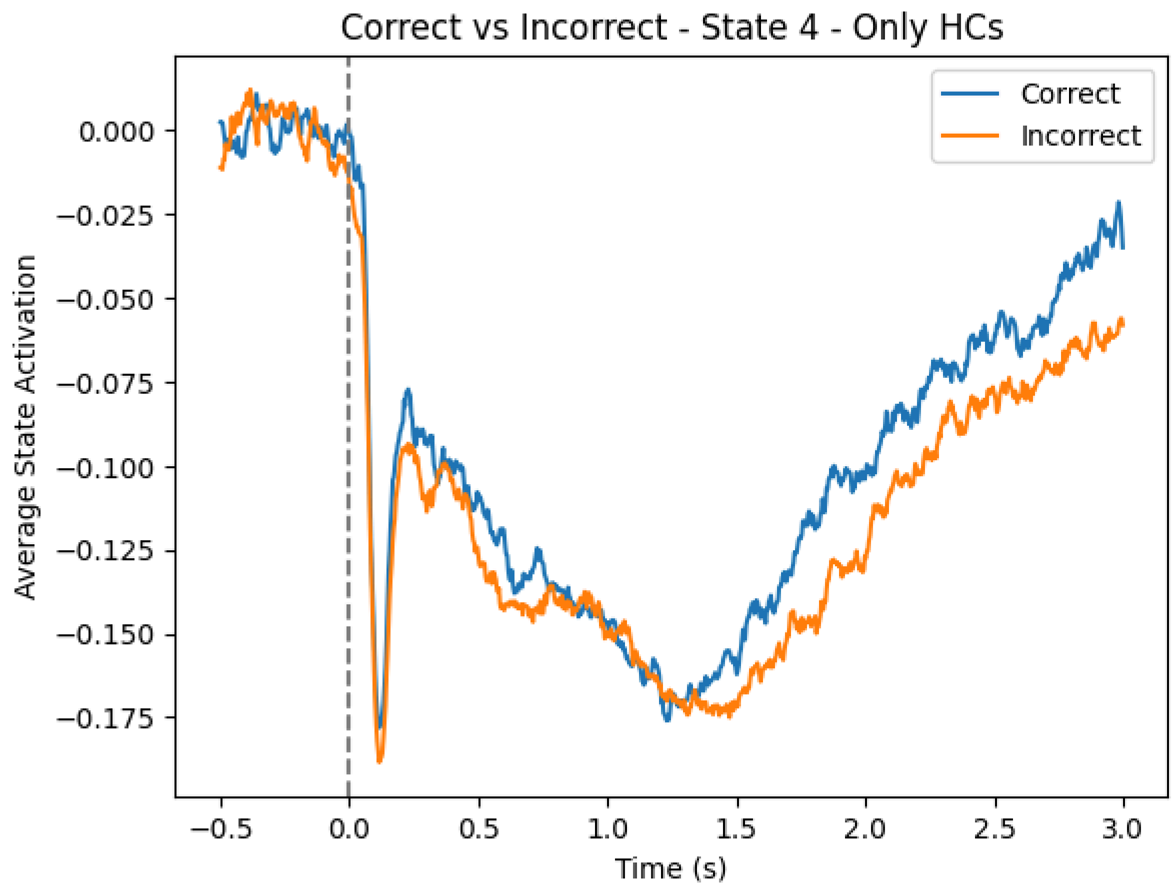
```
from collections import OrderedDict

## Plot RRMS vs. HC per state and group comparison stat. sign. diff.
for i in range(n_states):
```

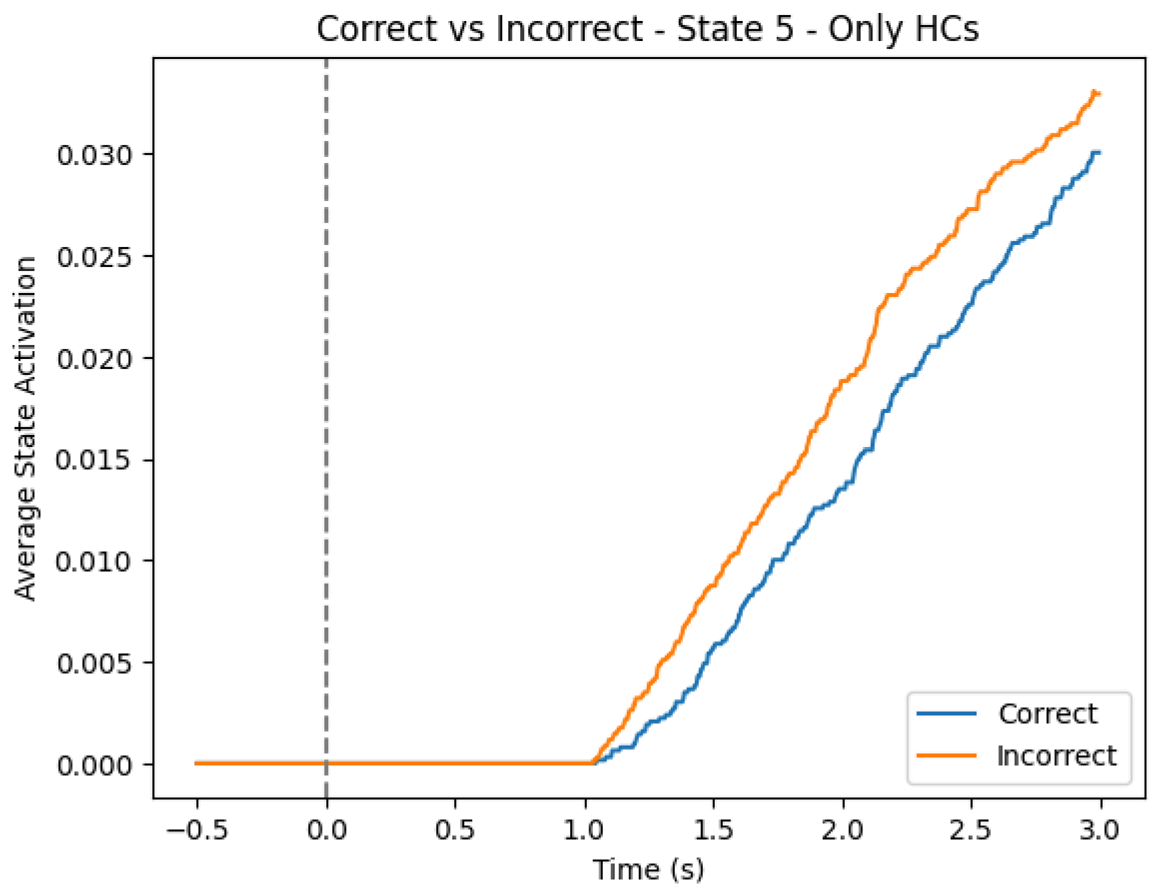
```
    plt.figure()
    plt.plot(t,avg_stc_epoch_correct[:,i],label='Correct')
    plt.plot(t,avg_stc_epoch_incorrect[:,i],label='Incorrect')
    plt.title(f'Correct vs Incorrect - State {i+1} - Only HCs')
    plt.xlabel('Time (s)')
    plt.ylabel('Average State Activation')
    plt.legend()
    plt.axvline(color="gray", linestyle="--")

    significant = stimulus_type_diff_pvals_HC[i] < 0.05
    sig_times = t[significant]
    draw = min(np.min(avg_stc_epoch_correct[:,i]), np.min(avg_stc_epoch_inco
    if len(sig_times) > 0:
        dt = t[1] - t[0]
        y = -0.025 + i * 0.01 + draw                # this value needs to b
        for st in sig_times:
            plt.plot((st - dt, st + dt), (y, y), linewidth=4, color='g', lab

        # StackOverflow fix to remove duplicate labels (due to ex. a for loo
        handles, labels = plt.gca().get_legend_handles_labels()
        by_label = OrderedDict(zip(labels, handles))
        plt.legend(by_label.values(), by_label.keys())
```

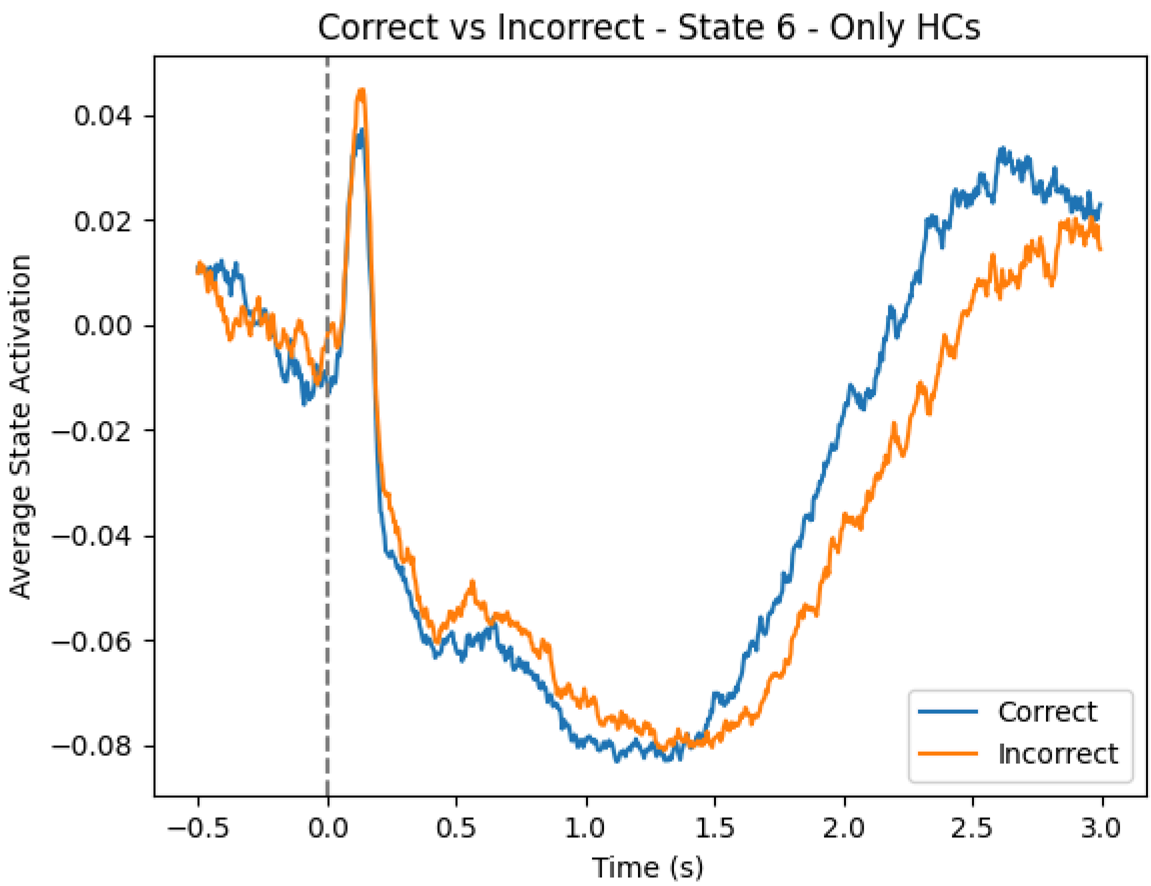


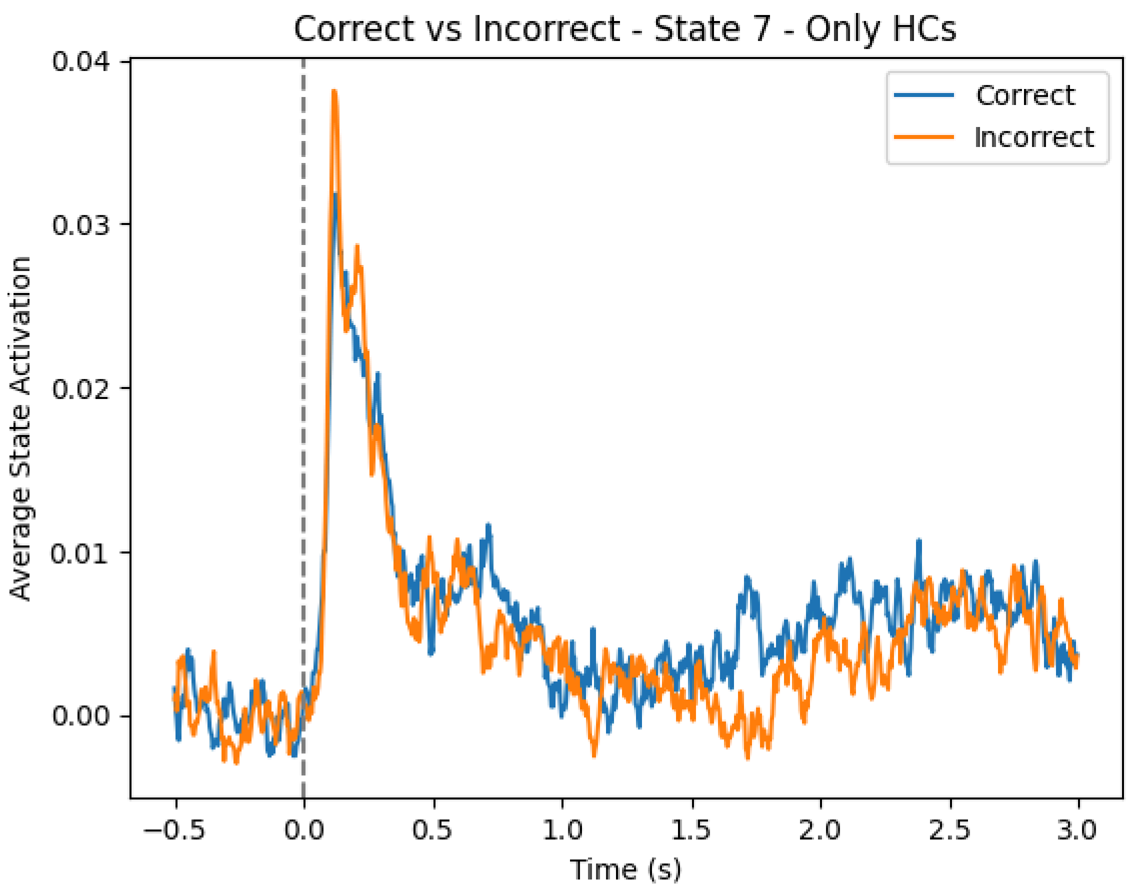

Correct vs Incorrect - State 2 - Only HCs
Correct
Incorrect
Average State Activation
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)

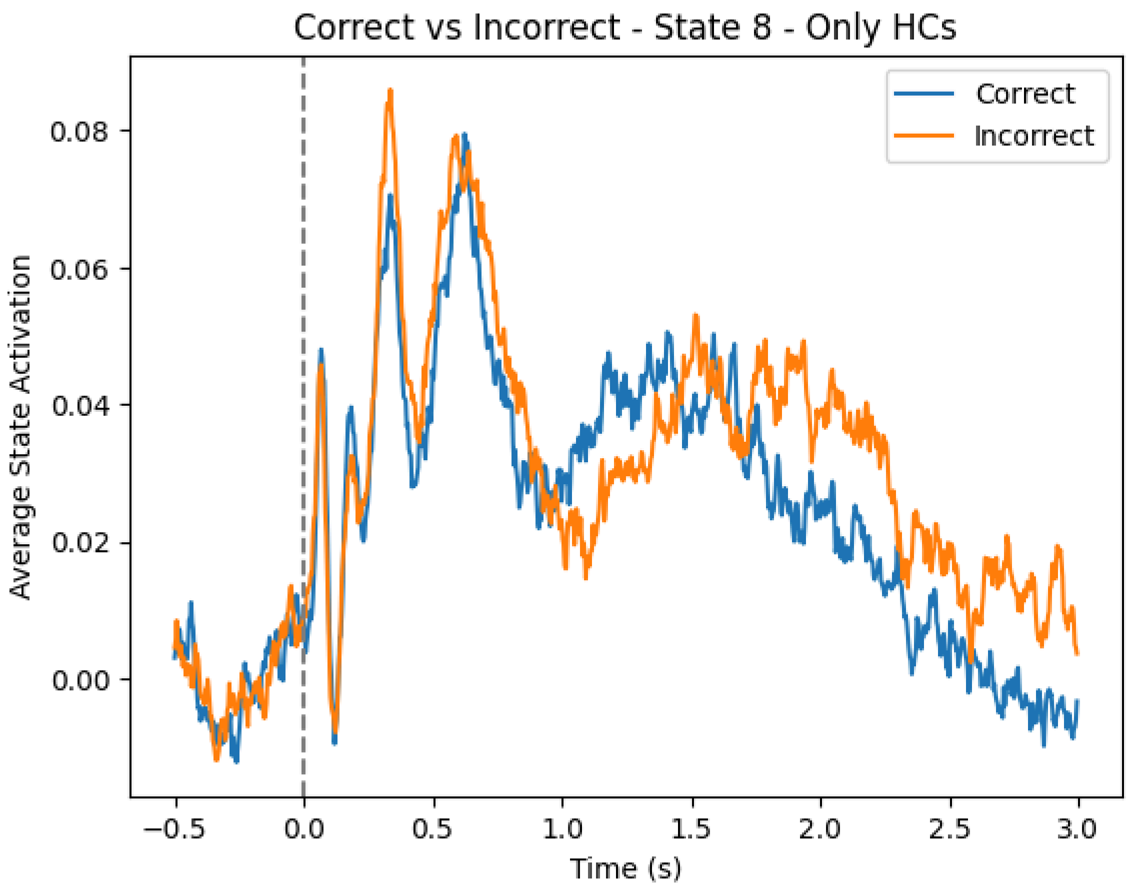

Correct vs Incorrect - State 3 - Only HCs
Correct
Incorrect
Average State Activation
0.3
0.2
0.1
0.0
−0.1
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Correct vs Incorrect - State 4 - Only HCs
Correct
Incorrect
Average State Activation
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
−0.150
−0.175
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Correct vs Incorrect - State 5 - Only HCs
Average State Activation
0.030
0.025
0.020
0.015
0.010
0.005
0.000
Correct
Incorrect
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Correct vs Incorrect - State 6 - Only HCs
Average State Activation
0.04
0.02
0.00
−0.02
−0.04
−0.06
−0.08
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)
Correct
Incorrect


Correct vs Incorrect - State 7 - Only HCs
Average State Activation
0.04
0.03
0.02
0.01
0.00
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)
Correct
Incorrect



Only MS

In [99]:
```
assignments_MS = []
for i in range(len(concatenated_epochs_corr_incorr)):
    if i < int(len(concatenated_epochs_corr_incorr)/2):
        if i in df_ms_idx:
            assignments_MS.append(1)
        else:
            assignments_MS.append(0)
    else:
        if i in np.array(df_control_idx) + int(len(concatenated_epochs_corr_
            assignments_MS.append(2)
        else:
            assignments_MS.append(0)
```

In [100…
```
## Max stat permutation testing for statistically significant differences
stimulus_type_diff_pvals_MS = []
for i in range(n_states):
    data_test = concatenated_epochs_corr_incorr[:,:,i]
    print(np.shape(data_test))

    # Do stats testing
    diff, pvalues = statistics.group_diff_max_stat_perm(
        data_test,
        assignments_MS,
        n_perm=5000,
    )
    stimulus_type_diff_pvals_MS.append(pvalues)
    print("Number of significant differences:", np.sum(pvalues < 0.05))
```

```
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 1
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 1
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
```

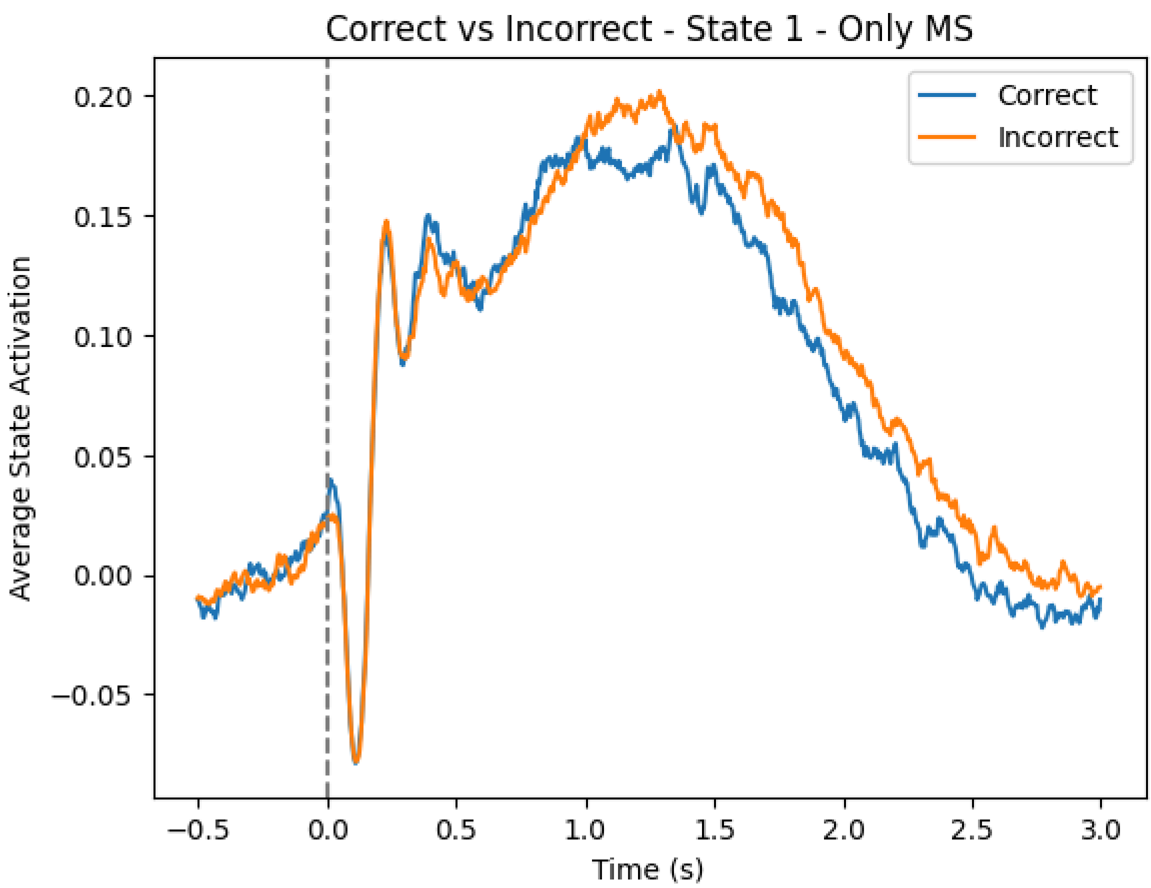
```
/home/olivierb/.local/lib/python3.9/site-packages/glmtools/fit.py:464: Ru
ntimeWarning: invalid value encountered in divide
  copes / denom,
```

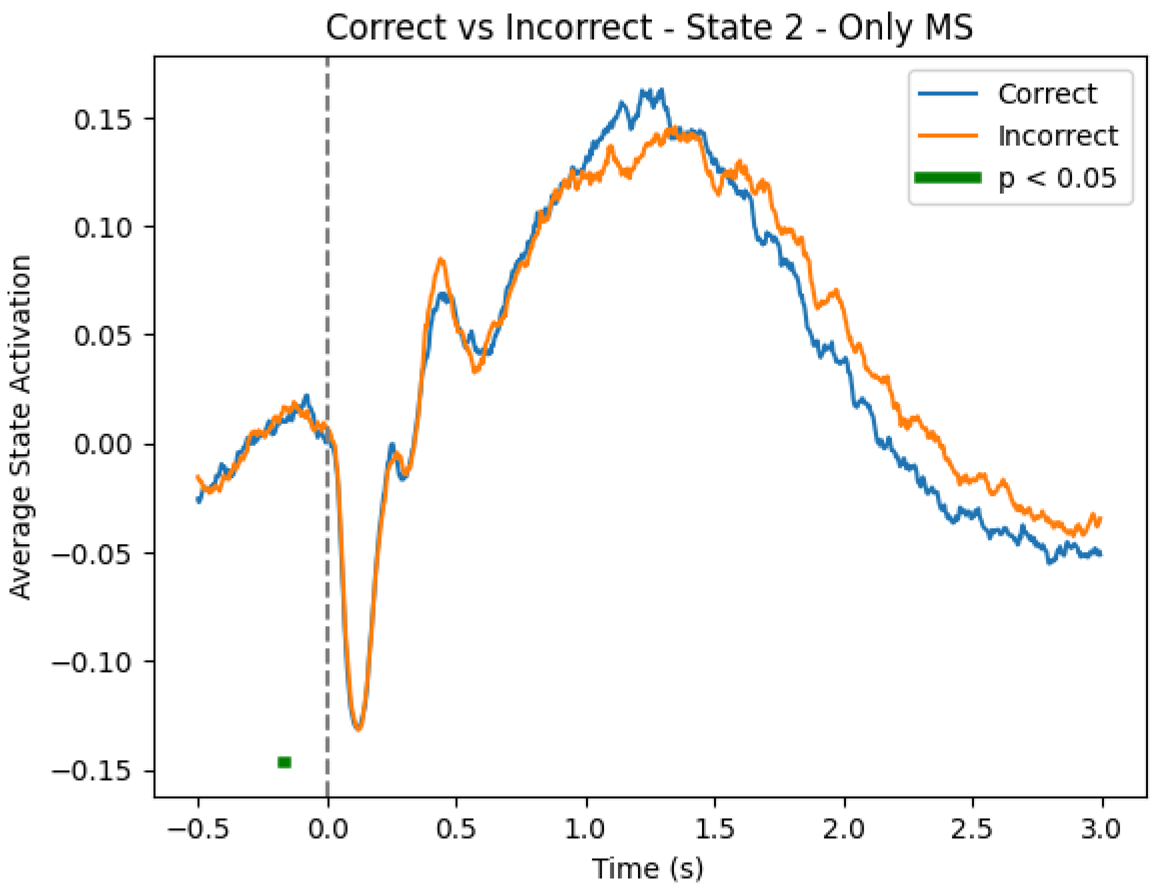
```
Using tstats as metric
Number of significant differences: 106
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
(220, 875)
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Different
ial) with mode=row-shuffle
        Computing 5000 permutations
        Taking max-stat across ['features 1'] dimensions
Using tstats as metric
Number of significant differences: 0
```

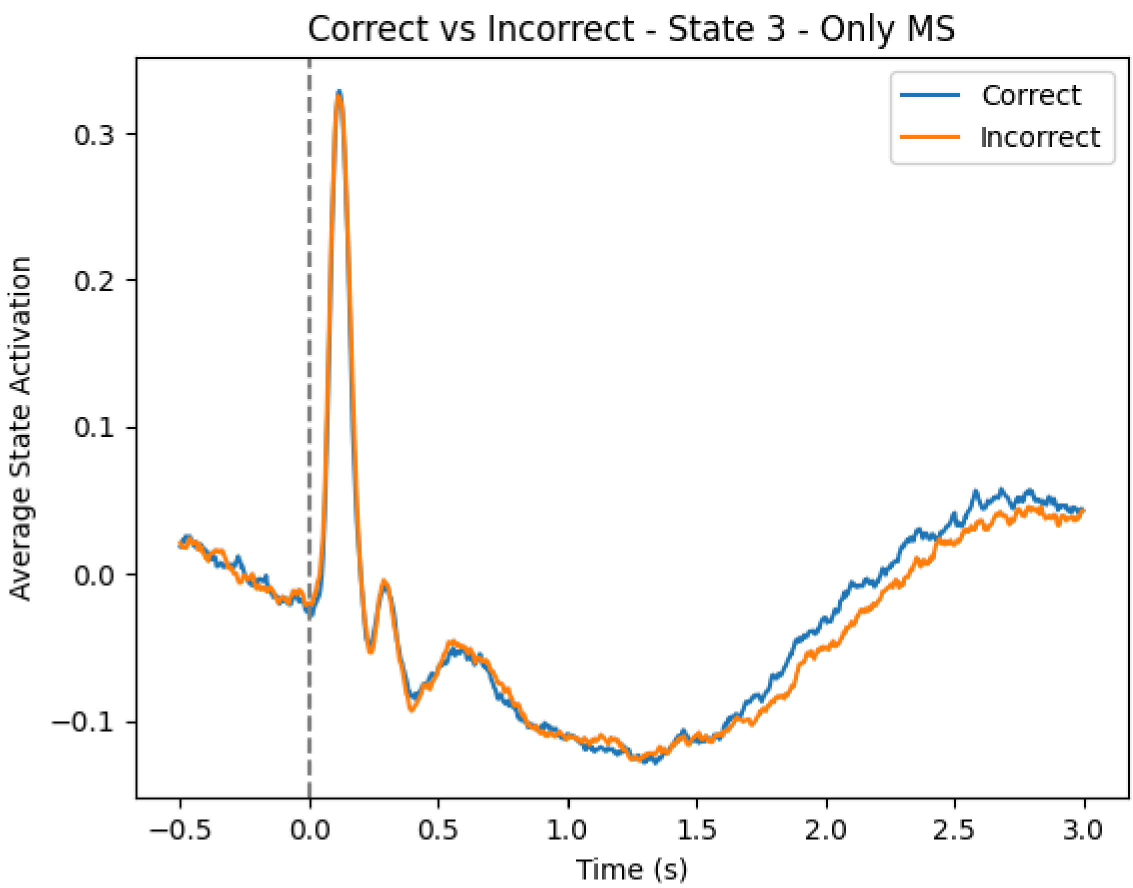
In [101…

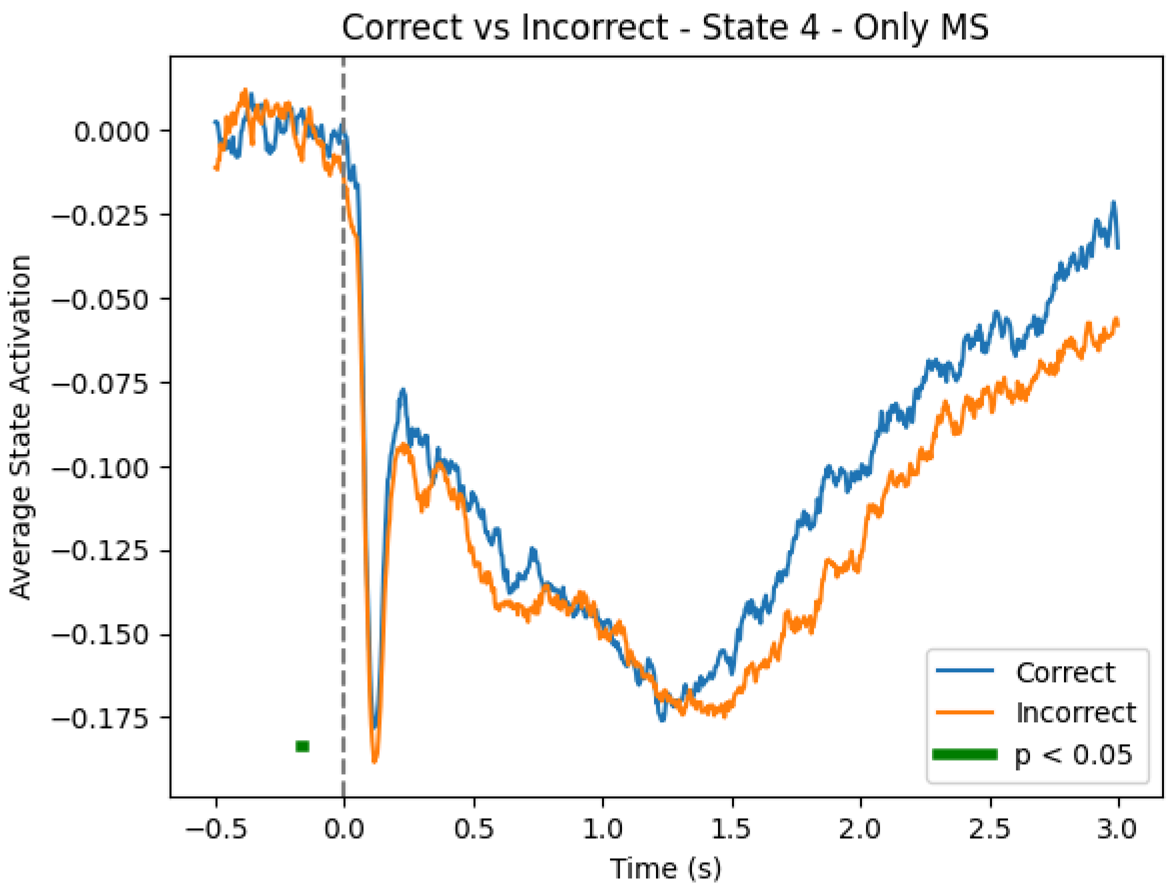
```
from collections import OrderedDict

## Plot RRMS vs. HC per state and group comparison stat. sign. diff.
for i in range(n_states):
```

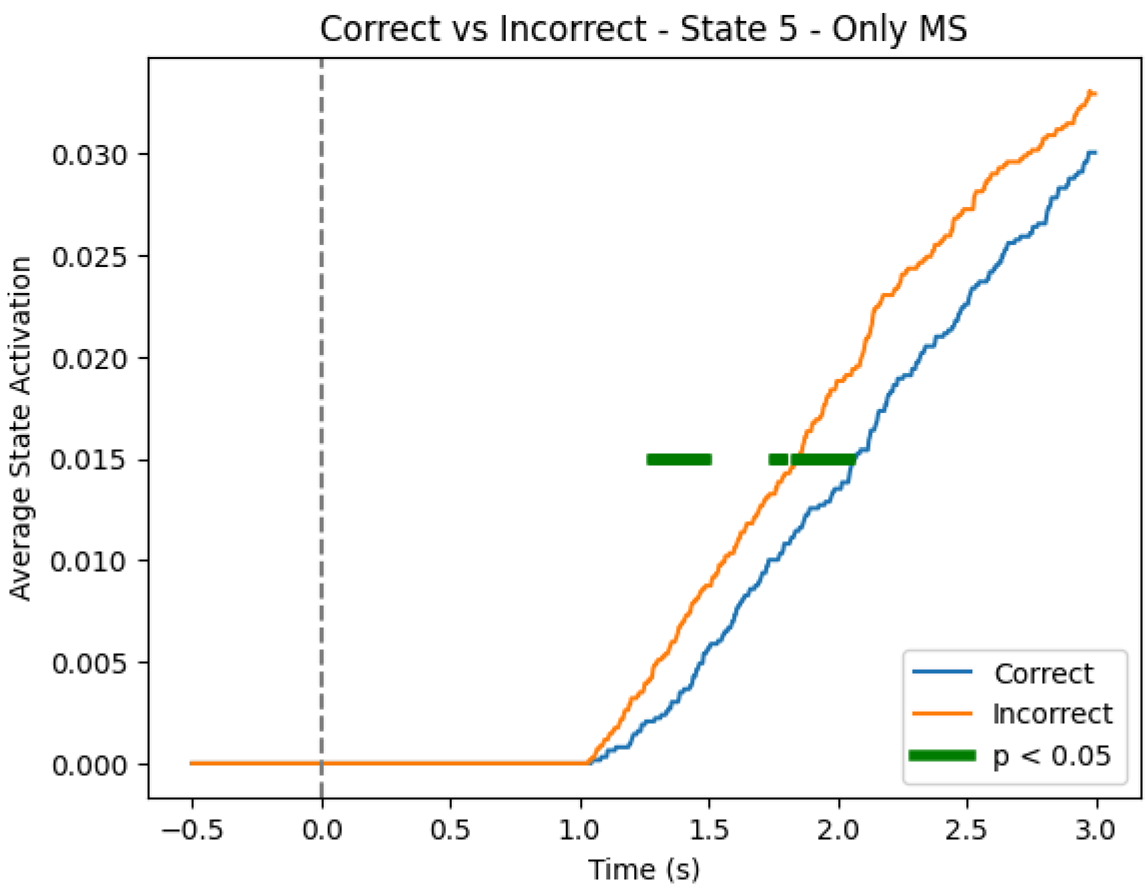
```
    plt.figure()
    plt.plot(t,avg_stc_epoch_correct[:,i],label='Correct')
    plt.plot(t,avg_stc_epoch_incorrect[:,i],label='Incorrect')
    plt.title(f'Correct vs Incorrect - State {i+1} - Only MS')
    plt.xlabel('Time (s)')
    plt.ylabel('Average State Activation')
    plt.legend()
    plt.axvline(color="gray", linestyle="--")

    significant = stimulus_type_diff_pvals_MS[i] < 0.05
    sig_times = t[significant]
    draw = min(np.min(avg_stc_epoch_correct[:,i]), np.min(avg_stc_epoch_inco
    if len(sig_times) > 0:
        dt = t[1] - t[0]
        y = -0.025 + i * 0.01 + draw                # this value needs to b
        for st in sig_times:
            plt.plot((st - dt, st + dt), (y, y), linewidth=4, color='g', lab

        # StackOverflow fix to remove duplicate labels (due to ex. a for loo
        handles, labels = plt.gca().get_legend_handles_labels()
        by_label = OrderedDict(zip(labels, handles))
        plt.legend(by_label.values(), by_label.keys())
```

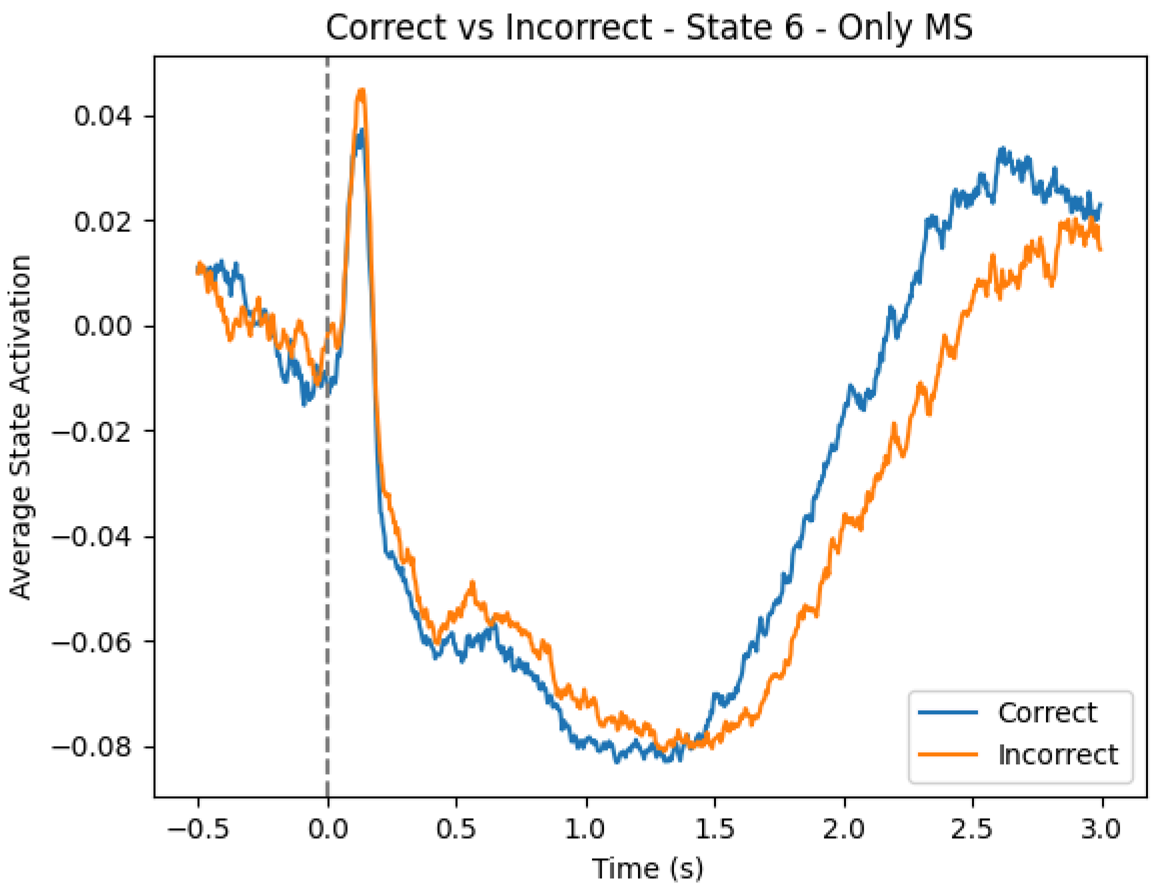


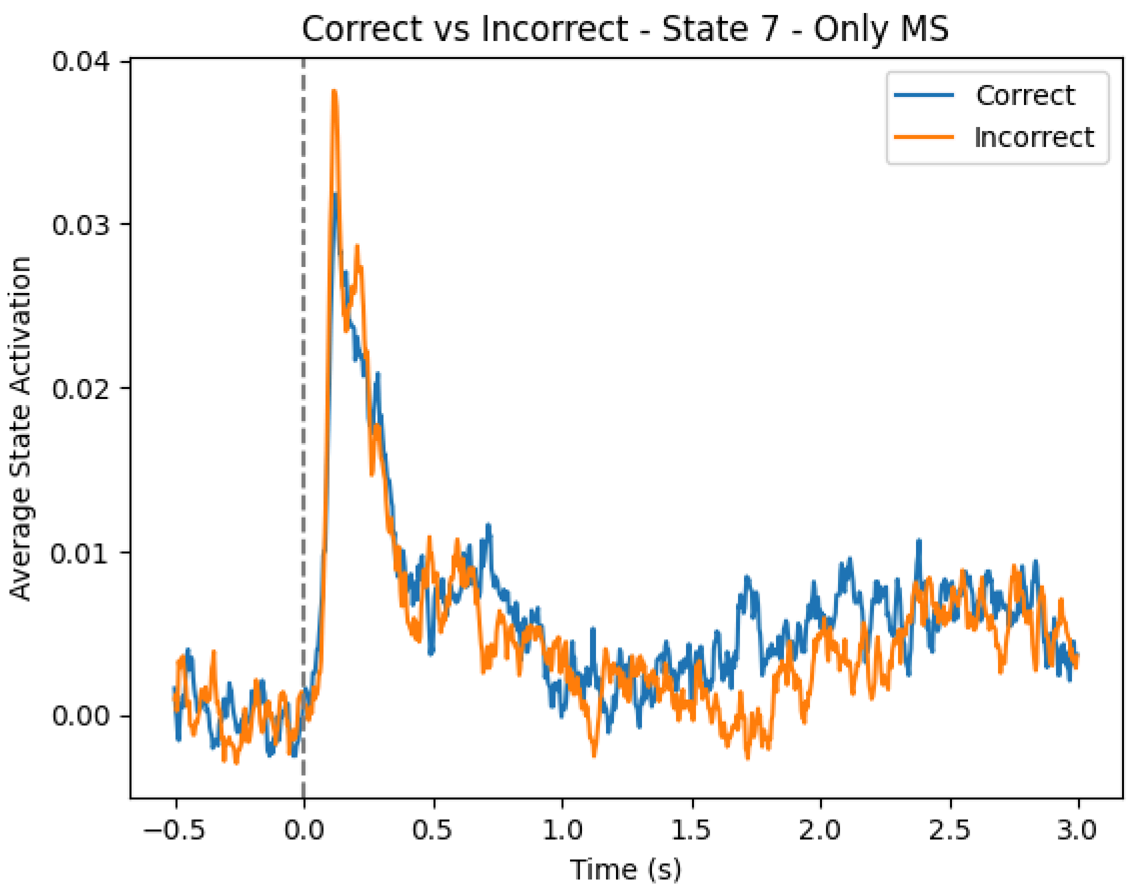

Correct vs Incorrect - State 2 - Only MS
Correct
Incorrect
p < 0.05
Average State Activation
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)

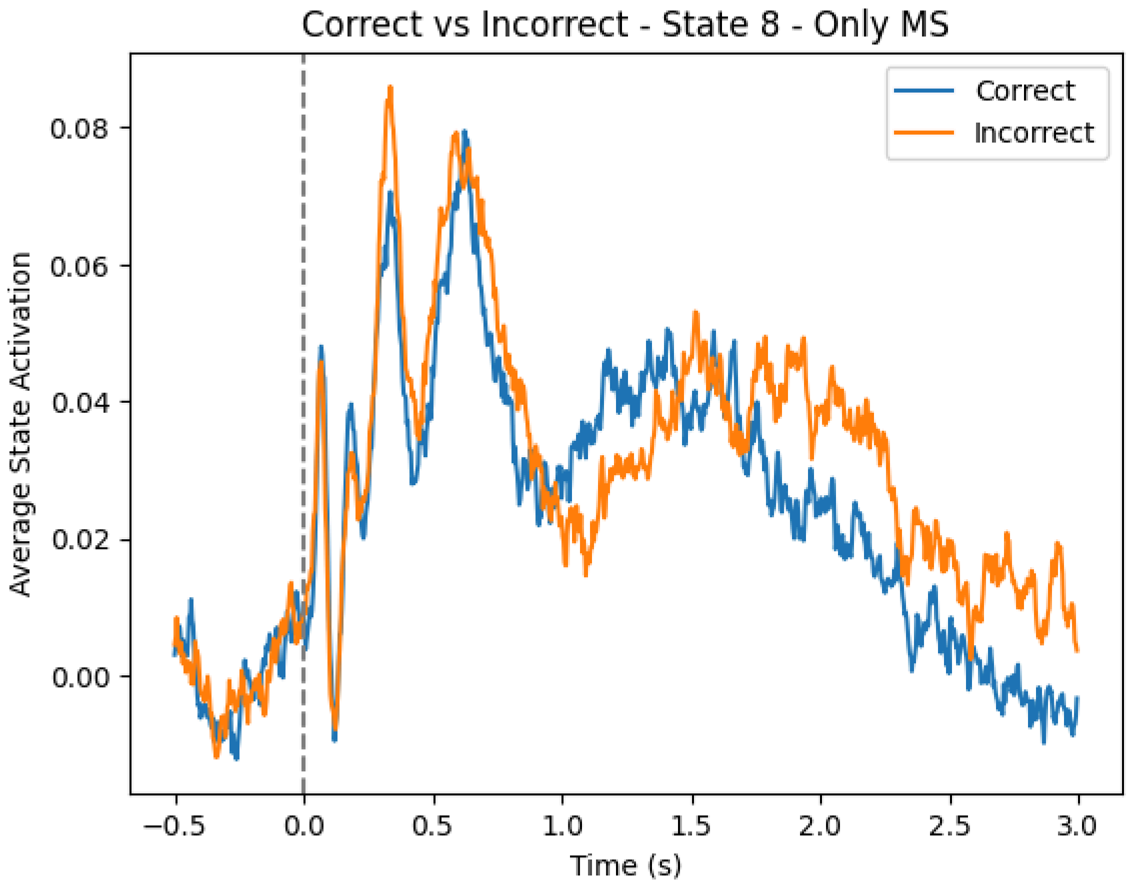

Correct vs Incorrect - State 3 - Only MS
Correct
Incorrect
Average State Activation
0.3
0.2
0.1
0.0
−0.1
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)


Correct vs Incorrect - State 4 - Only MS
Average State Activation
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
−0.150
−0.175
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)
Correct
Incorrect
p < 0.05


Correct vs Incorrect - State 5 - Only MS
Average State Activation
0.030
0.025
0.020
0.015
0.010
0.005
0.000
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time (s)
Correct
Incorrect
p < 0.05


Correct vs Incorrect - State 6 - Only MS
Average State Activation
Time (s)
Correct
Incorrect
0.04
0.02
0.00
−0.02
−0.04
−0.06
−0.08
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0


Correct vs Incorrect - State 7 - Only MS
Average State Activation
Time (s)
Correct
Incorrect
0.04
0.03
0.02
0.01
0.00
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0



3. Spatial Power maps & Coherence Networks

1. Calculate power spectra & coherences **between [1-45] Hz ==> This range can be chosen, and for preprocessing I used 0.01-70 Hz...**
2. Plot power spectra - per state
3. Plot power spectra - substract static power
4. Extract data-driven approach - spectral components
5. State power maps **per relevant spectral component**
   - SC1 (delta 1-4 Hz & theta 4-8 Hz)
   - SC2 (alpha 8-12 Hz)
   - SC3 beta (13-30 Hz)n_weights=True, # weighting for each subject when we average the spectra
6. Group differences **per oscillatory band**

First, calculate **power spectra & coherences** (this step also is a bit **time-consuming**)

In [18]:
```
from osl_dynamics.analysis import spectral

model = load(model_name)
data = model.get_training_time_series(training_data, prepared=False)

# Calculate multitaper spectra for each state and subject (will take a few m
f, psd, coh, w = spectral.multitaper_spectra(
    data=data,
```

```
    alpha=alpha,
    sampling_frequency=250,
    time_half_bandwidth=4,
    n_tapers=7,
    frequency_range=[1, 45],
    return_weights=True,   # weighting for each subject when we average the
    # can be chosen freely here -> set to [0,01 - 70] Hz ?????????????
)
```

```
2024-05-06 08:18:02 INFO osl-dynamics [mod_base.py:589:load]: Loading mod
el: Dynamic_Models/HMM_TDE_ALL_8states_25epochs
Calculating spectra: 100%|██████████| 110/110 [58:59<00:00, 32.18s/it]
```

In [19]:
```
# Saving as numpy files
import numpy as np
np.save(model_name + "/data/f.npy", f)
np.save(model_name + "/data/psd.npy", psd)
np.save(model_name + "/data/coh.npy", coh)
np.save(model_name + "/data/w.npy", w)

print(f.shape)
print(psd.shape)
print(coh.shape)
print(w.shape)
```

```
(88,)
(110, 8, 38, 88)
(110, 8, 38, 38, 88)
(110,)
```

In [105…
```
# Load in saved f, psd, coh
f = np.load(model_name + "/data/f.npy")
psd = np.load(model_name + "/data/psd.npy")
coh = np.load(model_name + "/data/coh.npy")
w = np.load(model_name + "/data/w.npy")
#wb_comp = np.load(model_name + "/data/nnmf.npy")  # (n_components, n_freq)
```

Data-driven approach to find frequency bands ==> Spectral factorization (Non-Negative Matrix Fractorization, NNMF)

Here you also choose n_components (= 4)

Try out 4 Spectral Components

In [106…
```
from osl_dynamics.analysis import spectral

# Perform NNMF on the coherence spectra of each subject (we concatenate each
wb_comp = spectral.decompose_spectra(coh, n_components=4) # into 4 frequency
print(wb_comp.shape)
```

```
2024-05-06 12:27:40 INFO osl-dynamics [spectral.py:895:decompose_spectra]:
Performing spectral decomposition
(4, 88)
```

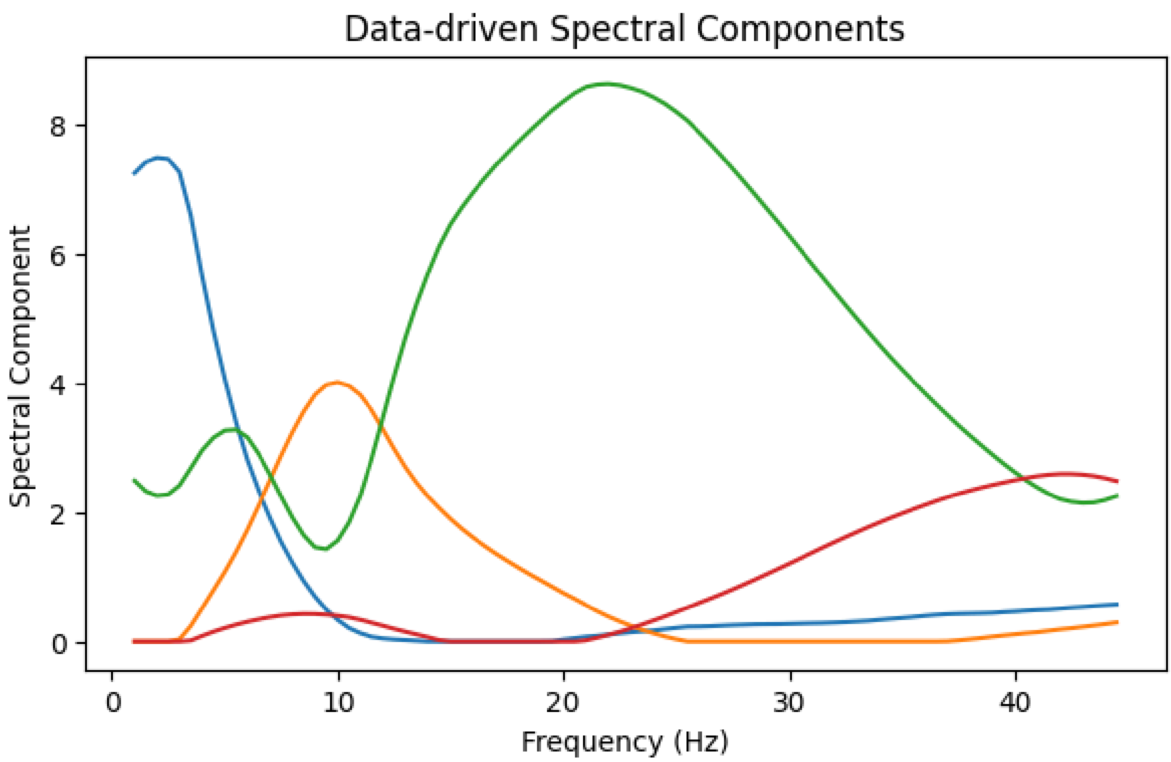
In [107…
```
np.save(model_name + "/data/wb_comp.npy", wb_comp)
```

In [108…
```
from osl_dynamics.utils import plotting

plotting.plot_line(
    [f, f, f, f],  # we need to repeat 4x because 4 components were fitted
```

```
    wb_comp,
    x_label="Frequency (Hz)",
    y_label="Spectral Component",
    title="Data-driven Spectral Components"
)

#np.save(model_name + "/data/nnmf.npy", wb_comp)
```

Out[108]:

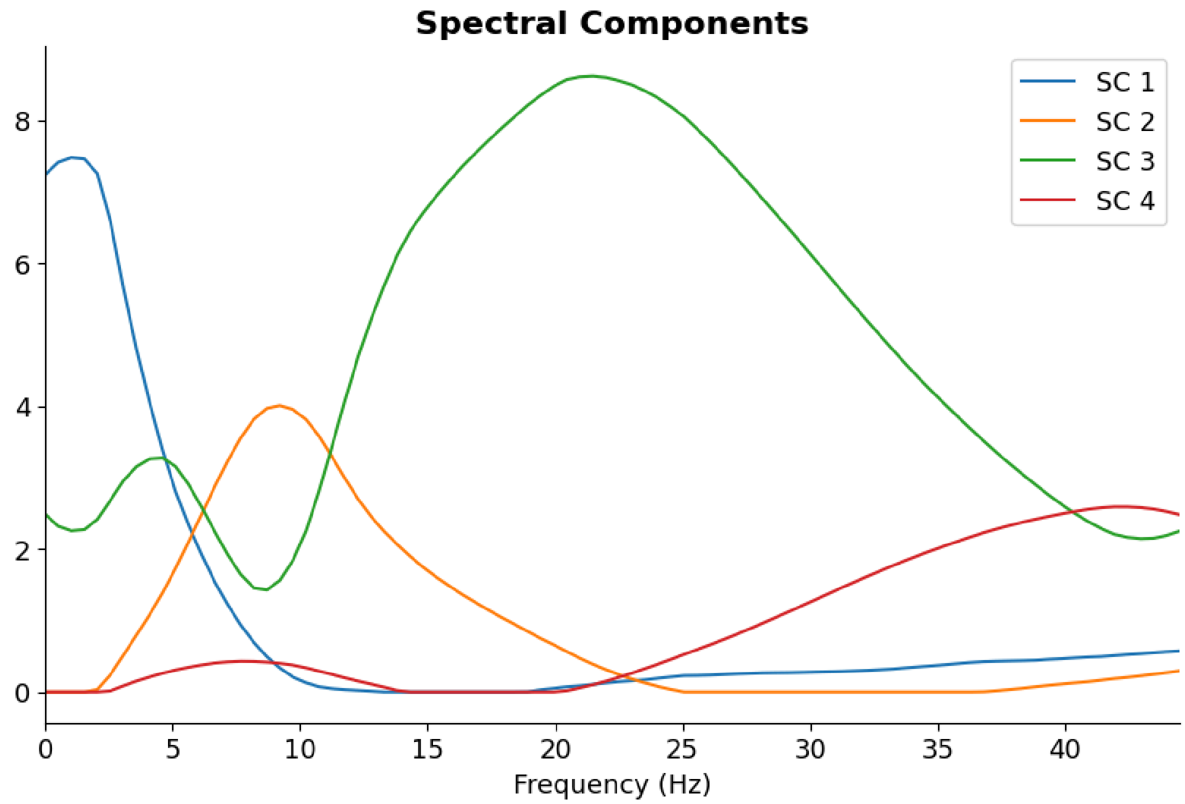
```
(<Figure size 700x400 with 1 Axes>,
 <Axes: title={'center': 'Data-driven Spectral Components'}, xlabel='Freq
uency (Hz)', ylabel='Spectral Component'>)
```



a few extra plots using the Spectral Components

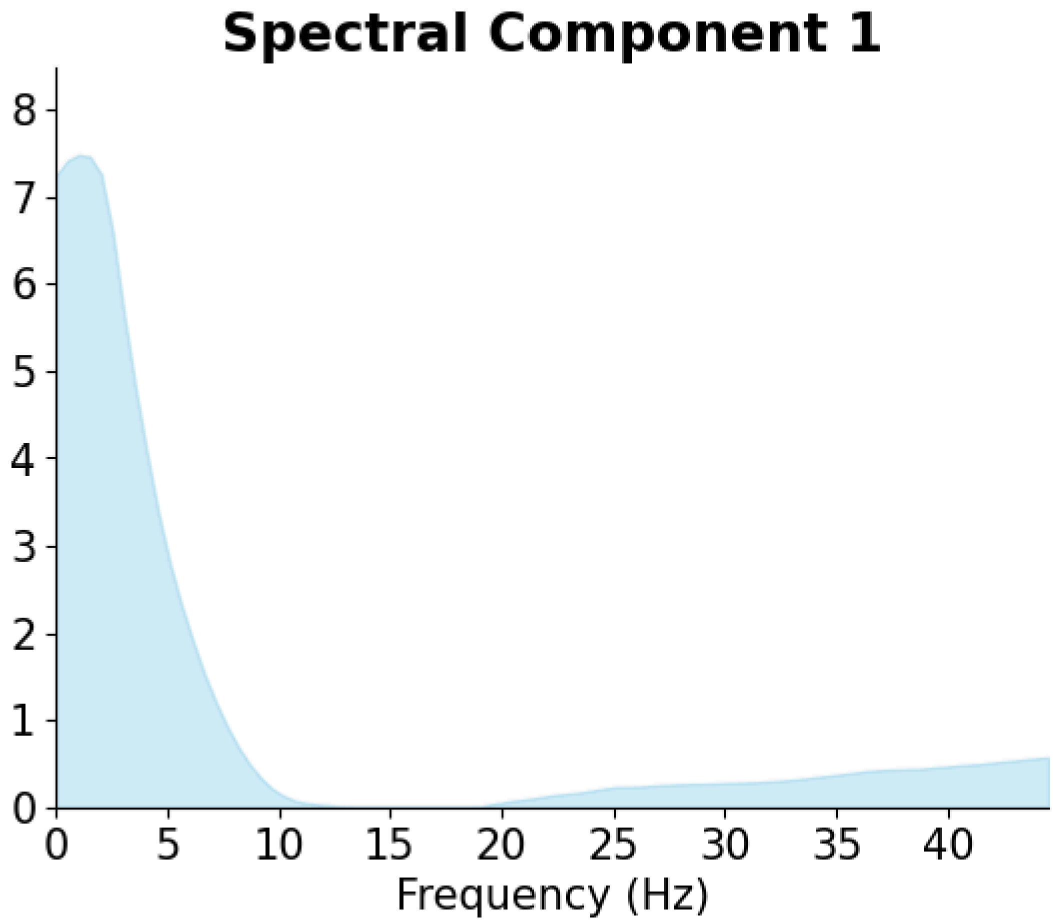
In [109…

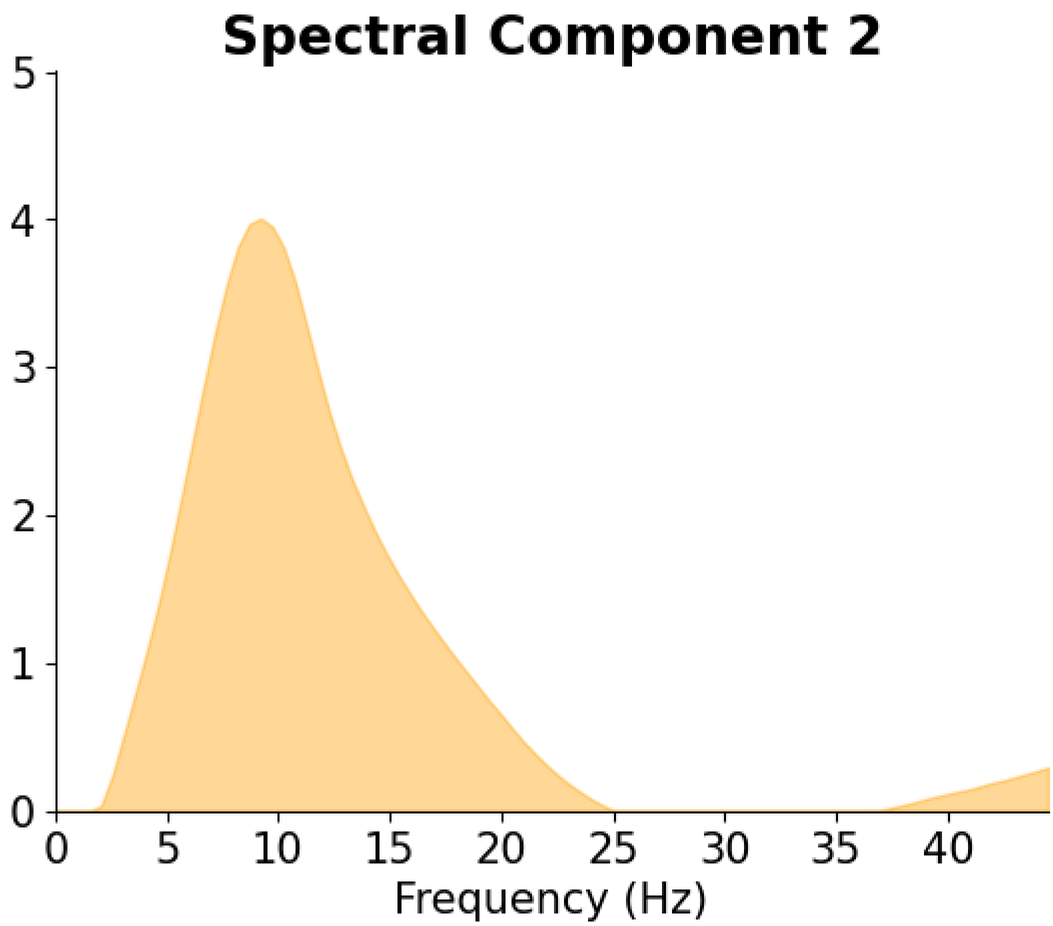
```
f_plot = np.linspace(0, f[-1], len(wb_comp[0]))
colors = ['tab:blue', 'tab:orange', 'tab:green', 'tab:red']
plt.figure(figsize=(10,6))

# Plot all spectral components:
for sc in range(len(wb_comp)):
    plt.plot(f_plot, wb_comp[sc], color=colors[sc], label=f'SC {sc+1}')

plt.xlabel('Frequency (Hz)', fontsize=13)
plt.xticks(fontsize=13)
plt.yticks(fontsize=13)
plt.xlim([0,f_plot[-1]])
plt.title('Spectral Components' , weight='bold', fontsize=16)
plt.gca().spines['top'].set_visible(False)    # Hide the top spine
plt.gca().spines['right'].set_visible(False)  # Hide the right spine
plt.legend(fontsize=13)
plt.show()
```

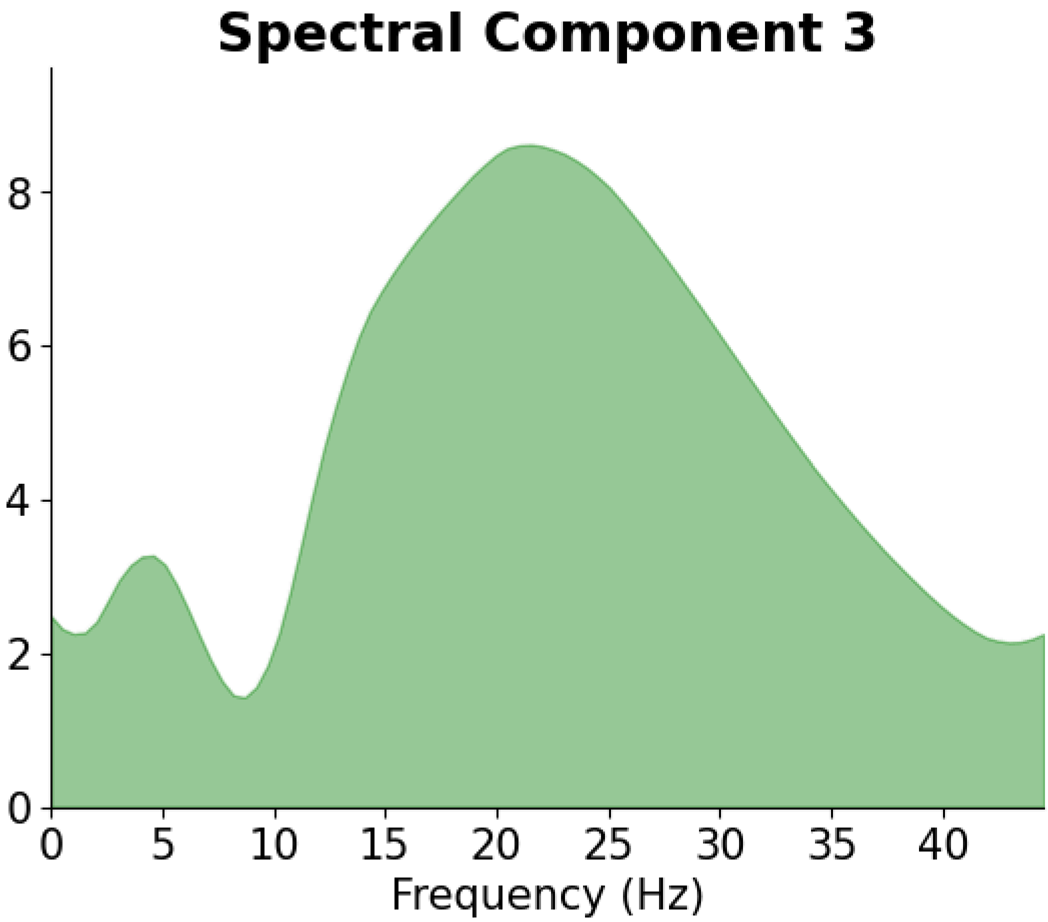


In [110…

```
f_plot = np.linspace(0, f[-1], len(wb_comp[0]))
colors = ['skyblue', 'orange', 'green']

# Plot the first 3 spectral components:
for sc in range(len(wb_comp) - 1):
    plt.figure()
    plt.plot(f_plot, wb_comp[sc], color=colors[sc], alpha=0.01)
    plt.xlabel('Frequency (Hz)', fontsize=15)
    plt.xticks(fontsize=15)
    plt.yticks(fontsize=15)
    plt.xlim([0,f_plot[-1]])
    plt.ylim([0,np.max(wb_comp[sc])+1])
    plt.fill_between(f_plot, wb_comp[sc], color=colors[sc], alpha=0.4)  # Fi
    plt.title('Spectral Component {}'.format(sc+1), weight='bold', fontsize=
    plt.gca().spines['top'].set_visible(False)    # Hide the top spine
    plt.gca().spines['right'].set_visible(False)  # Hide the right spine
    plt.show()
```


Spectral Component 1
8
7
6
5
4
3
2
1
0
0 5 10 15 20 25 30 35 40
Frequency (Hz)


Spectral Component 2
5
4
3
2
1
0
0 5 10 15 20 25 30 35 40
Frequency (Hz)



Plot **MEAN** power spectra

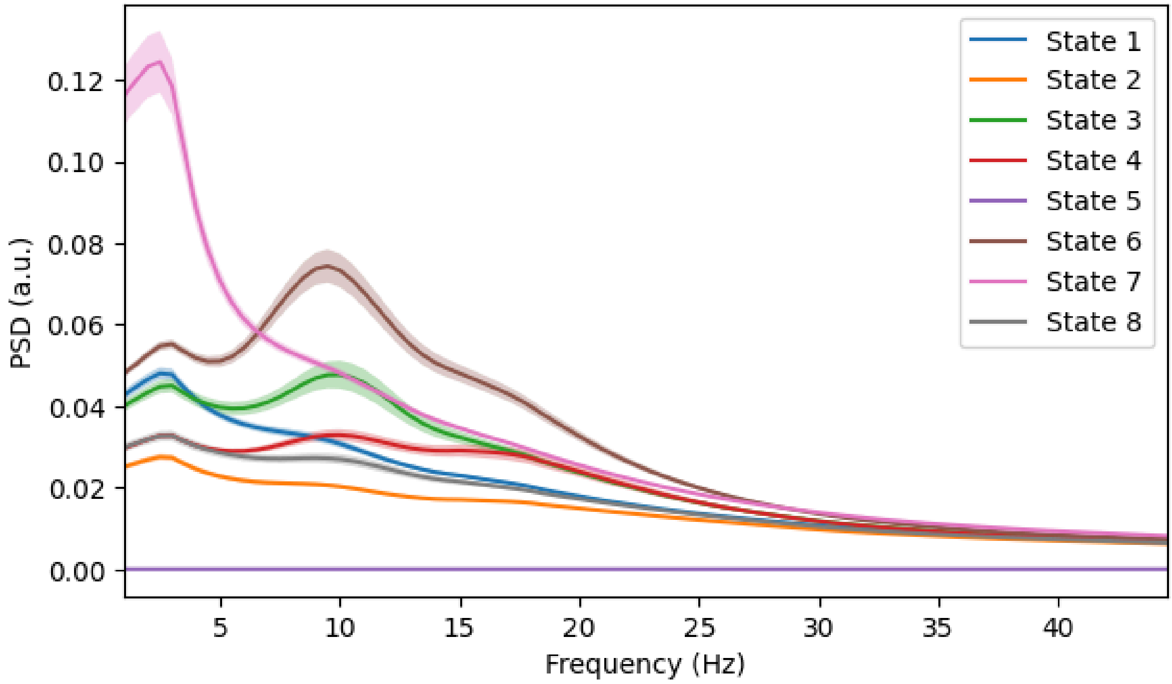
In [111…

```
from osl_dynamics.utils import plotting

# Average over subjects and channels
psd_mean = np.mean(psd, axis=(0,2))
print(psd_mean.shape)

# Also get mean across channels and the standard error
gpsd = np.average(psd, axis=0, weights=w)
p = np.mean(gpsd, axis=-2)
e = np.std(gpsd, axis=-2) / np.sqrt(gpsd.shape[-2])

# Plot
n_states = psd_mean.shape[0]
plotting.plot_line(
    [f] * n_states,
    p,
    errors=[p-e, p+e],
    labels=[f"State {i}" for i in range(1, n_states + 1)],
    x_label="Frequency (Hz)",
    y_label="PSD (a.u.)",
    x_range=[f[0], f[-1]],
)
```

```
(8, 88)
```

Out[111]:

```
(<Figure size 700x400 with 1 Axes>,
 <Axes: xlabel='Frequency (Hz)', ylabel='PSD (a.u.)'>)
```



Same plot WITHOUT FLAT State

In [112…

```
print(e[np.array([True, True, True, True, False, True, True, True])].shape)
```

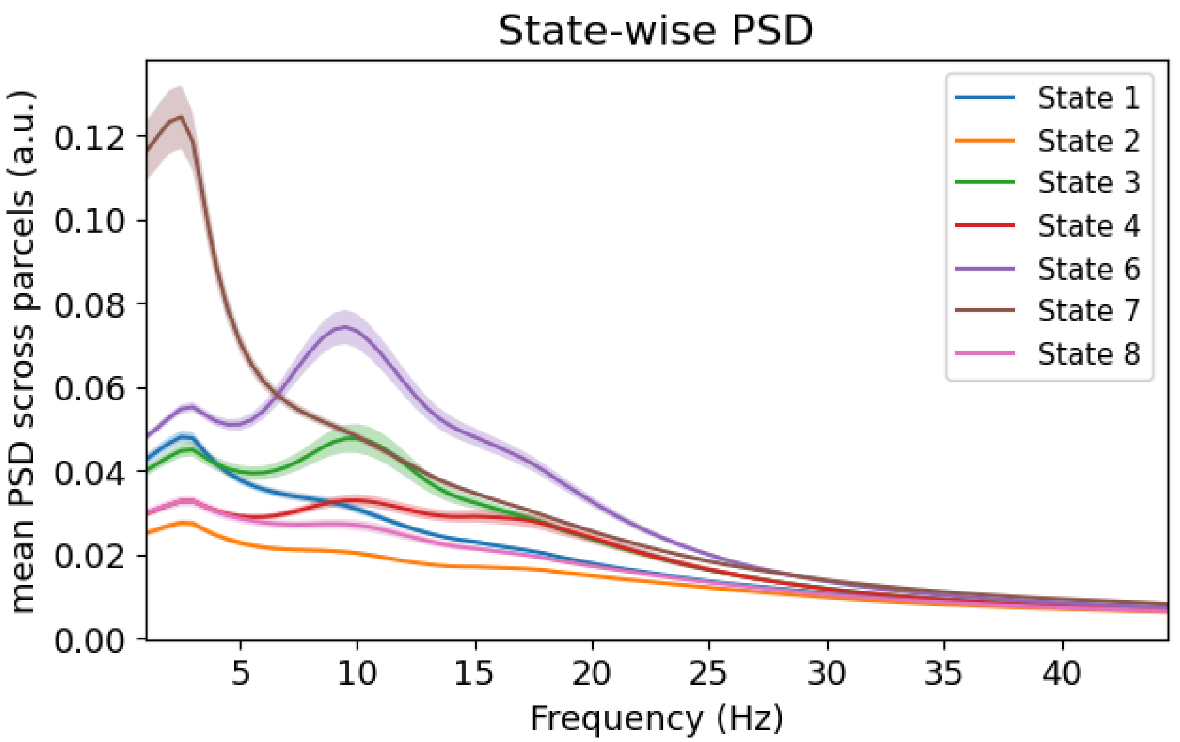
```
(7, 88)
```

In [114…

```
# Average over subjects and channels
psd_mean = np.mean(psd, axis=(0,2))
print(psd_mean.shape)

# Also get mean across channels and the standard error
gpsd = np.average(psd, axis=0, weights=w)
p = np.mean(gpsd, axis=-2)
e = np.std(gpsd, axis=-2) / np.sqrt(gpsd.shape[-2])

p_NEW = p[np.array([True, True, True, True, False, True, True, True])]
e_NEW = e[np.array([True, True, True, True, False, True, True, True])]


# Plot
n_states = psd_mean.shape[0] - 1
plotting.plot_line(
    [f] * n_states,
    p_NEW,
    errors=[p_NEW-e_NEW, p_NEW+e_NEW],
    labels=[f"State {i}" for i in [1, 2, 3, 4, 6, 7, 8]],
    x_label="Frequency (Hz)",
    y_label="PSD (a.u.)",
    x_range=[f[0], f[-1]],
)
# Access the ax object
ax = plt.gca()

# Set the fontsize for title, axis labels, and legend labels
ax.set_title("State-wise PSD", fontsize=16)
ax.set_xlabel("Frequency (Hz)", fontsize=13)
ax.set_ylabel("mean PSD scross parcels (a.u.)", fontsize=13)
ax.set_xticklabels(ax.get_xticklabels(), fontsize=13)
ax.set_yticklabels(ax.get_yticklabels(), fontsize=13)
ax.legend(fontsize=11)
```

```
(8, 88)
/tmp/ipykernel_2243037/3243611992.py:32: UserWarning: set_ticklabels() sh
ould only be used with a fixed number of ticks, i.e. after set_ticks() or
using a FixedLocator.
  ax.set_xticklabels(ax.get_xticklabels(), fontsize=13)
/tmp/ipykernel_2243037/3243611992.py:33: UserWarning: set_ticklabels() sh
ould only be used with a fixed number of ticks, i.e. after set_ticks() or
using a FixedLocator.
  ax.set_yticklabels(ax.get_yticklabels(), fontsize=13)
```

Out[114]:
```
<matplotlib.legend.Legend at 0x7fd337fa3310>
```



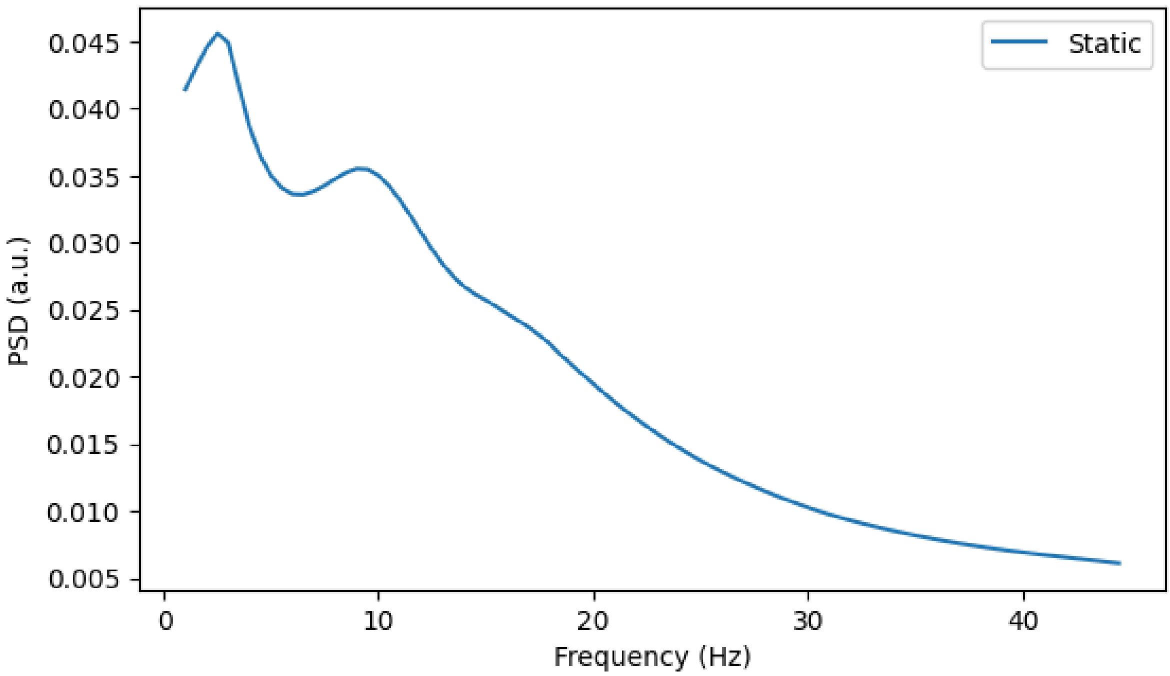
Substract the static power spectrum from each state-specific power spectrum ==> To get a flavour of the **state-specific oscillatory activity**

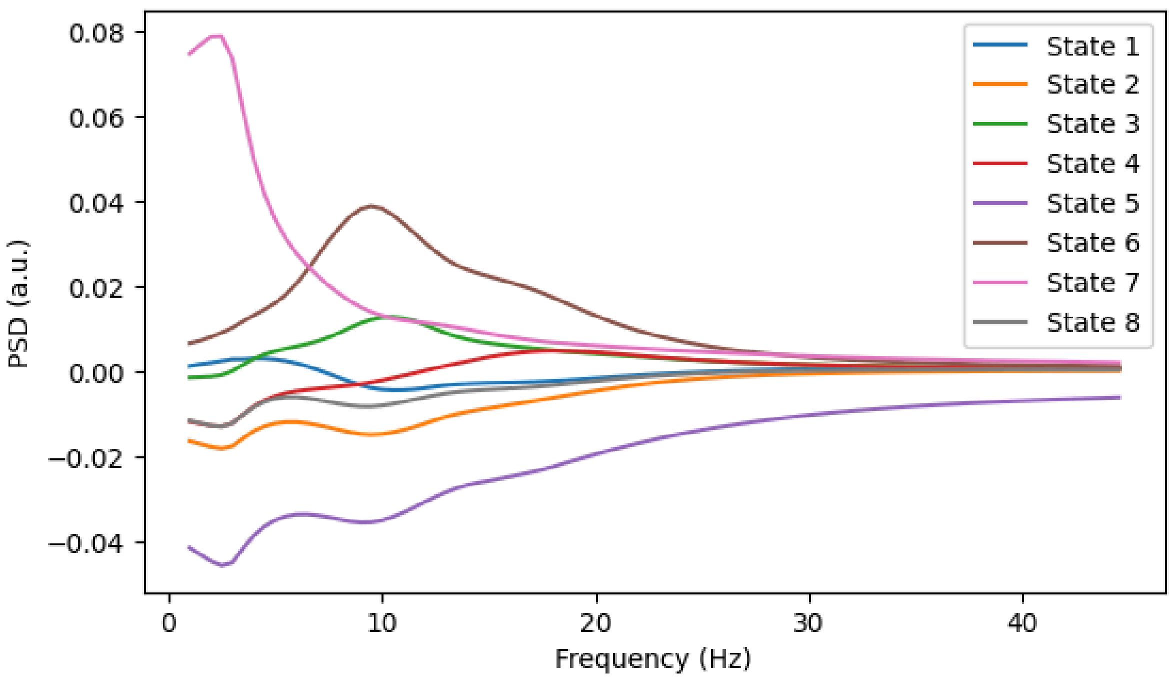
In [119…

```
# Average over subjects and channels
psd_mean = np.mean(psd, axis=(0,2))
print(psd_mean.shape)

# Also get mean across channels and the standard error

gpsd = np.average(psd, axis=0, weights=w)
p = np.mean(gpsd, axis=-2)
e = np.std(gpsd, axis=-2) / np.sqrt(gpsd.shape[-2])

# Calculate static PSD and average over channels
gpsd_static = np.mean(gpsd, axis=0)
static_p = np.mean(gpsd_static, axis=0)

# Calculate state PSDs relative to the static PSD
p_rel_mean = p - static_p[np.newaxis, ...]

n_states = 8
# Plot
fig, ax = plotting.plot_line(
    [f],
    [static_p],
    labels=["Static"],
    x_label="Frequency (Hz)",
    y_label="PSD (a.u.)",
```

```
)
fig, ax = plotting.plot_line(
    [f] * n_states,
    p_rel_mean,
    labels=[f"State {i + 1}" for i in range(n_states)],
    x_label="Frequency (Hz)",
    y_label="PSD (a.u.)",
)
```

```
(8, 88)
```





Plot **MEAN** Coherence across all channels

In [122…

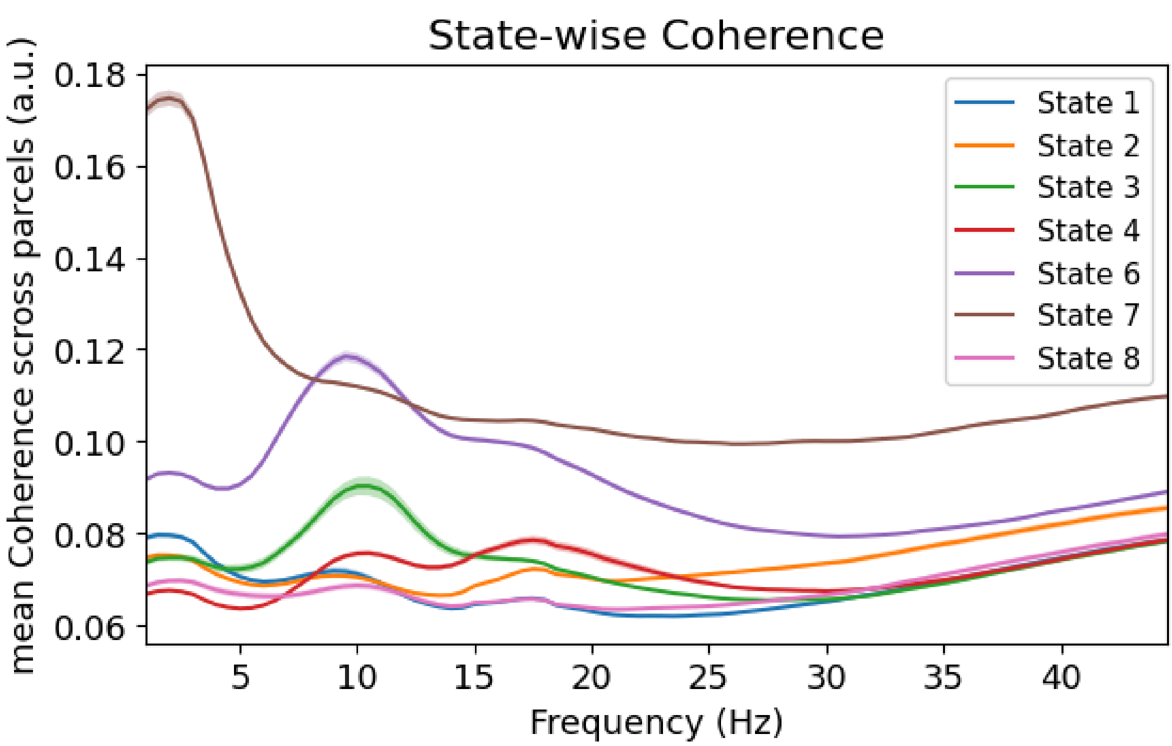
```
coh_across_chans = np.mean(np.mean(coh, axis=0),axis=(1,2))
print(np.shape(coh_across_chans))

gcoh = np.mean(np.mean(coh, axis=0), axis=1)
plot_coh = np.mean(gcoh, axis=-2)
e = np.std(gcoh, axis=-2) / np.sqrt(gcoh.shape[-2])
```

```
# Concatenate - remove State 3 because it has a coherence of almost 1 at all
plot_coh_concat = np.concatenate((plot_coh[:4], plot_coh[5:]), axis=0)
e_concat = np.concatenate((e[:4], e[5:]), axis=0)
n_states = 8

# Plot
plotting.plot_line(
    [f] * (n_states-1),
    plot_coh_concat,
    errors=[plot_coh_concat-e_concat, plot_coh_concat+e_concat],
    labels=[f"State {i}" for i in [1, 2, 3, 4, 6, 7, 8]],
    x_label="Frequency (Hz)",
    y_label="Coherence across all channels (a.u.)",
    x_range=[f[0], f[-1]],
)

# Access the ax object
ax = plt.gca()

# Set the fontsize for title, axis labels, and legend labels
ax.set_title("State-wise Coherence", fontsize=16)
ax.set_xlabel("Frequency (Hz)", fontsize=13)
ax.set_ylabel("mean Coherence scross parcels (a.u.)", fontsize=13)
ax.set_xticklabels(ax.get_xticklabels(), fontsize=13)
ax.set_yticklabels(ax.get_yticklabels(), fontsize=13)
ax.legend(fontsize=11)
```

```
(8, 88)
```

```
/tmp/ipykernel_2243037/4039232285.py:31: UserWarning: set_ticklabels() should only be used with a fixed number of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax.set_xticklabels(ax.get_xticklabels(), fontsize=13)
/tmp/ipykernel_2243037/4039232285.py:32: UserWarning: set_ticklabels() should only be used with a fixed number of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax.set_yticklabels(ax.get_yticklabels(), fontsize=13)
```

Out[122]: `<matplotlib.legend.Legend at 0x7fd337cc7a30>`



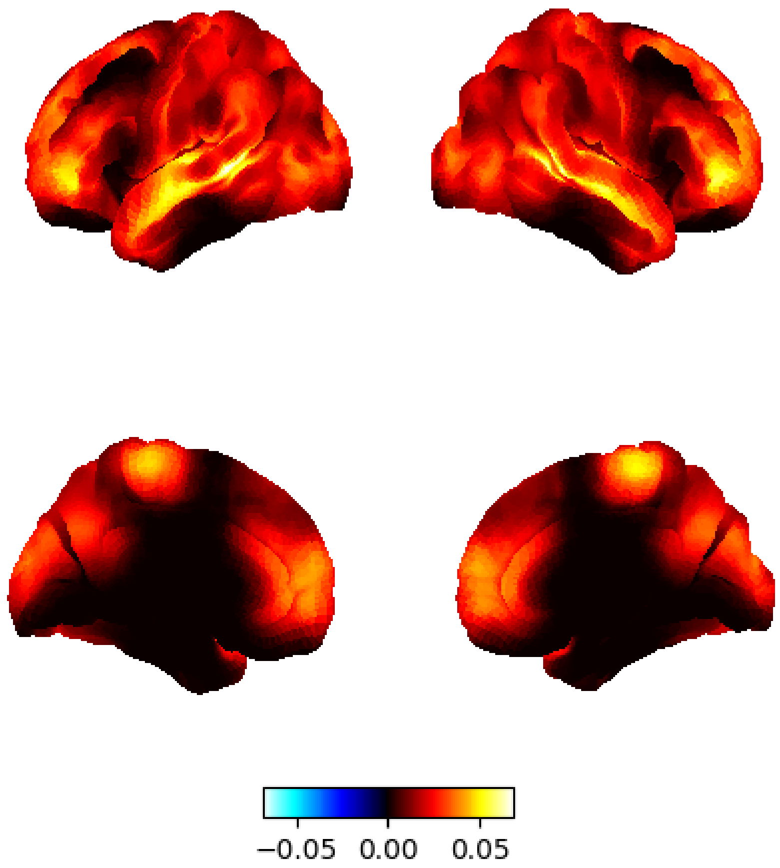
State Power maps + Coherence Networks ==> Spectral Component-specific

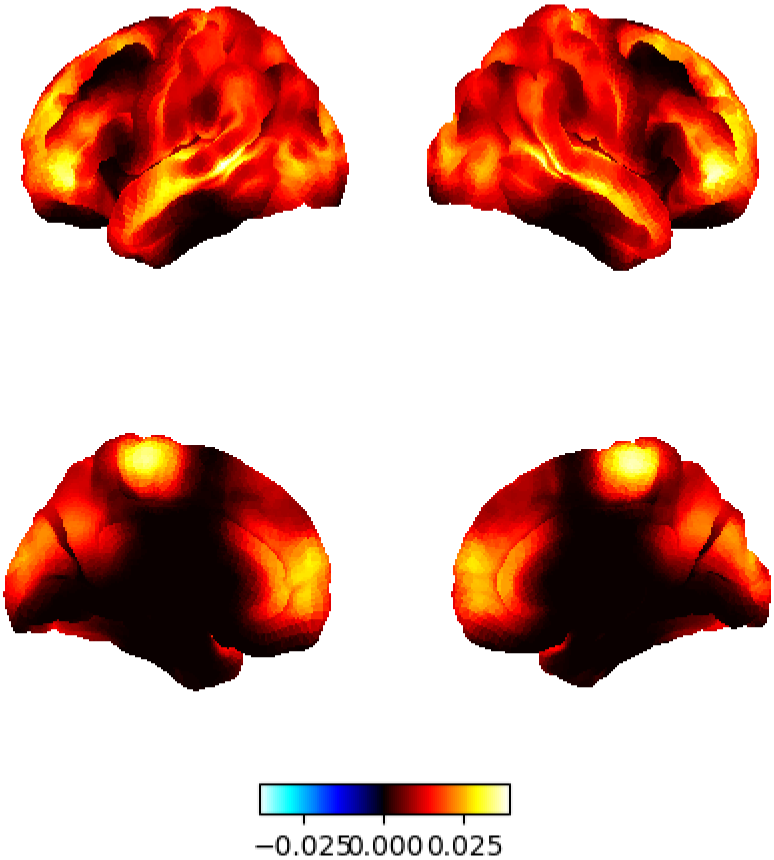
Spectral Component 1

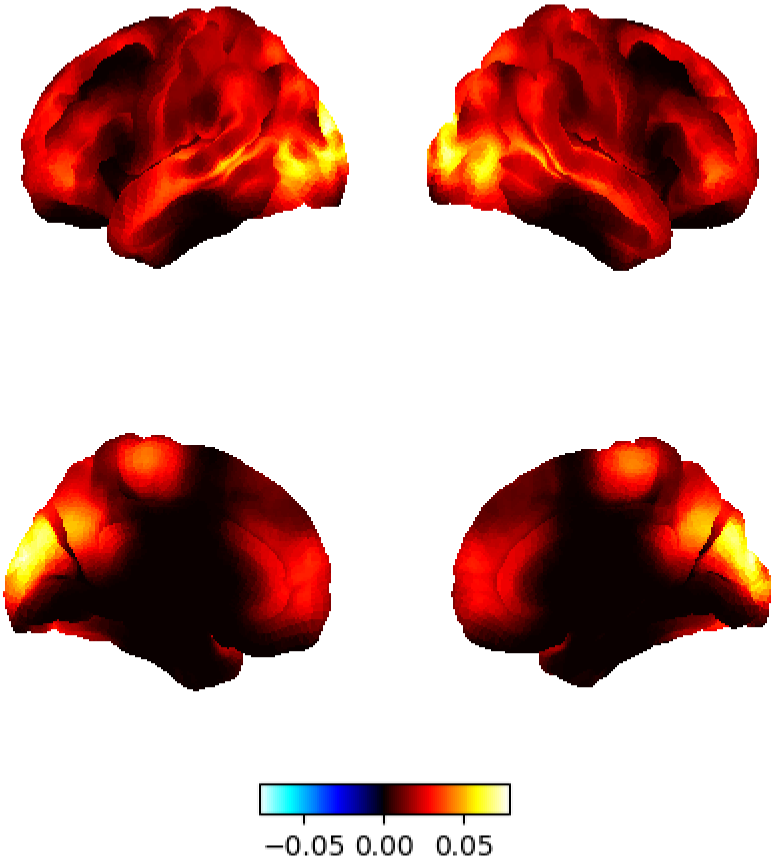
In [123…
```
# Integrate the power spectra over a frequency range, weighted by the specti
p_sc_all = power.variance_from_spectra(f, gpsd, wb_comp)
p_sc1 = p_sc_all[0]
```

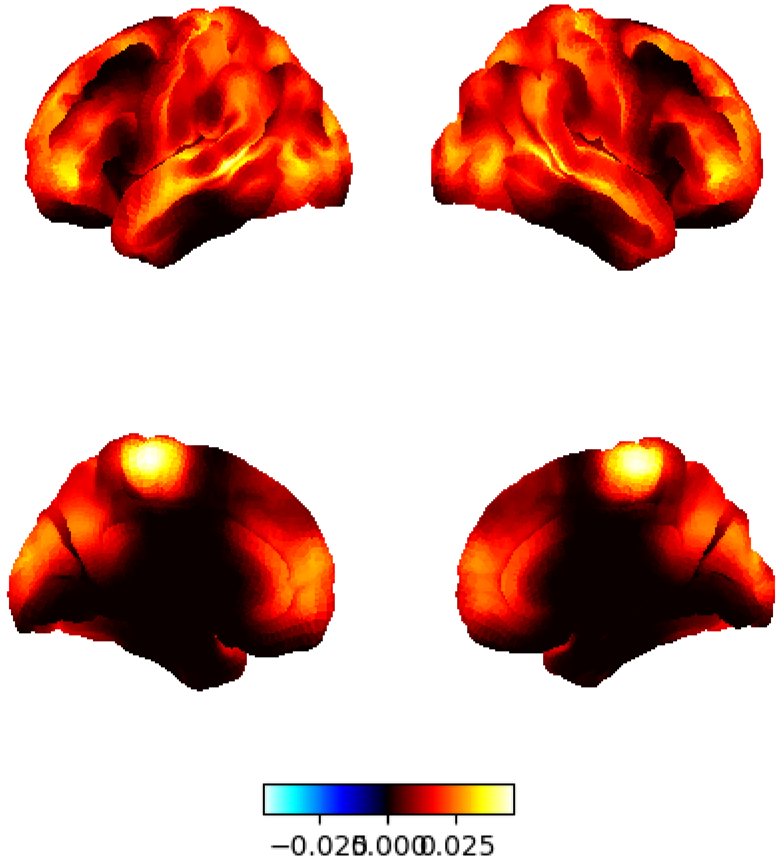
In [126…
```
## Plotting power maps (averages over all subjects) per state
fig, ax = power.save(
    p_sc1,
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
)
```

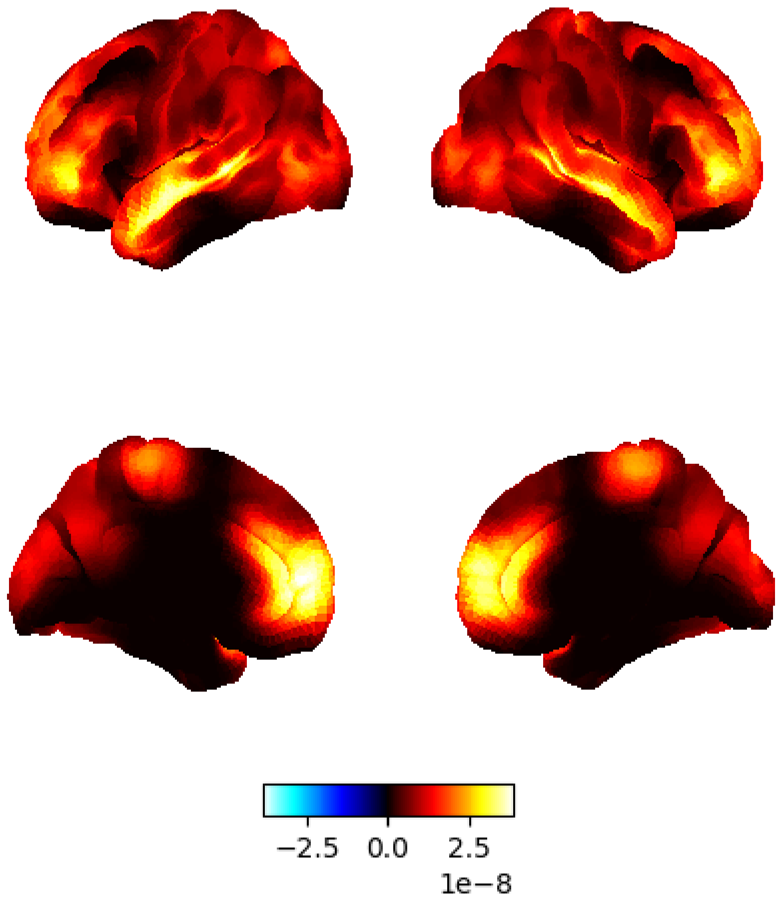
```
Saving images: 100%|██████████| 8/8 [00:08<00:00,  1.02s/it]
```

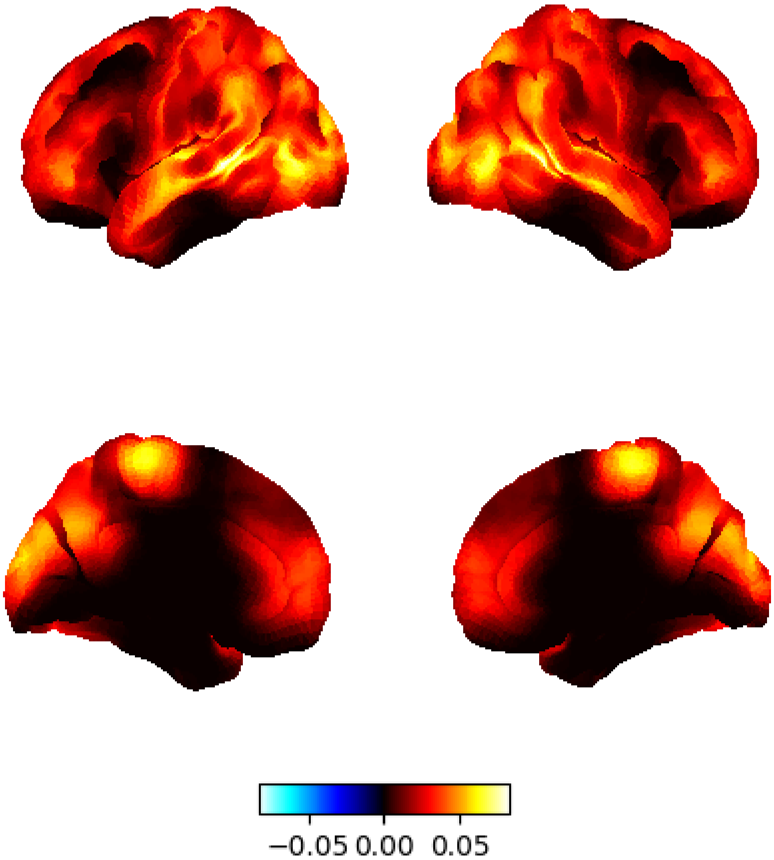


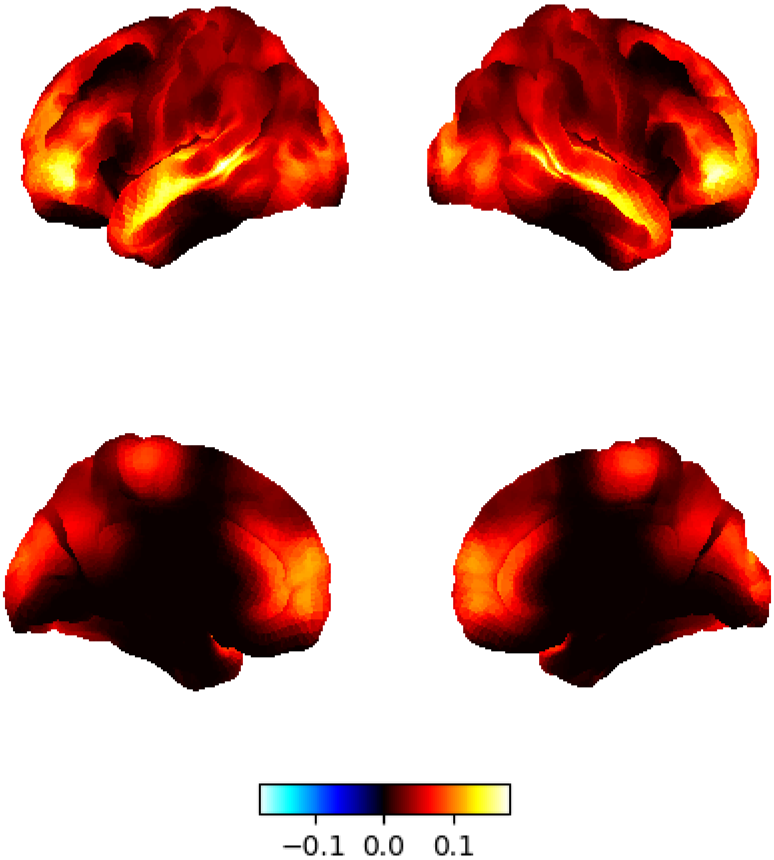

−0.025
0.000
0.025

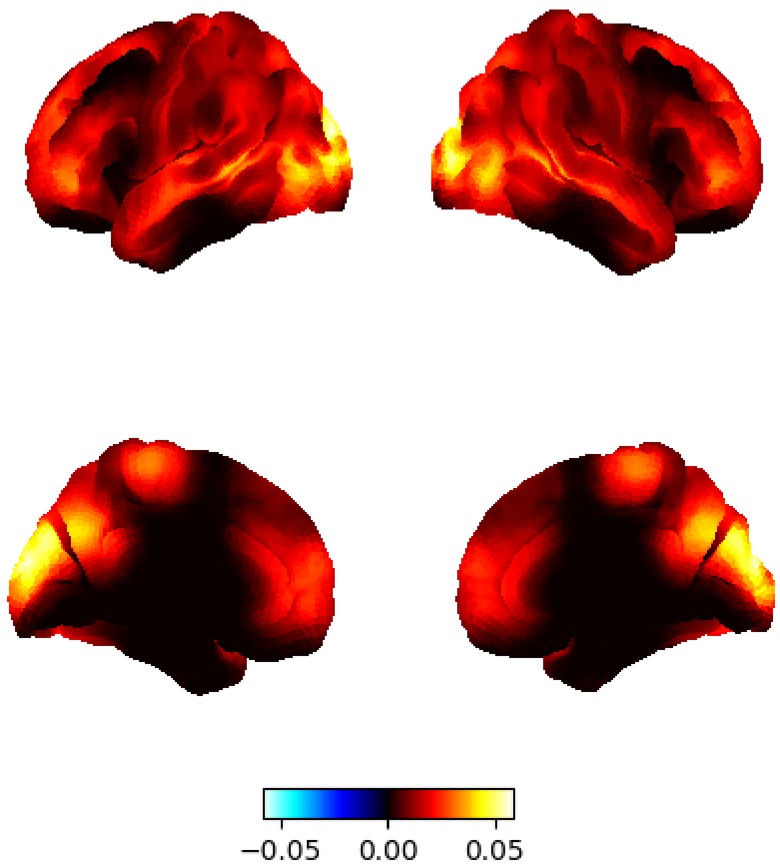

−0.05
0.00
0.05


−0.025
0.000
0.025


−2.5
0.0
2.5
1e−8


−0.05 0.00 0.05


−0.1 0.0 0.1

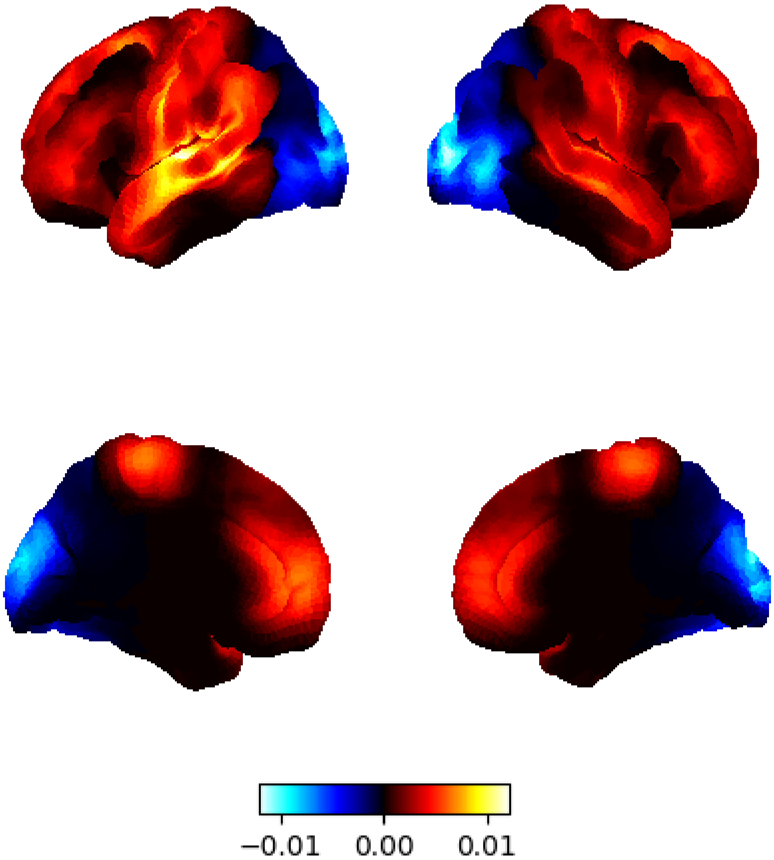


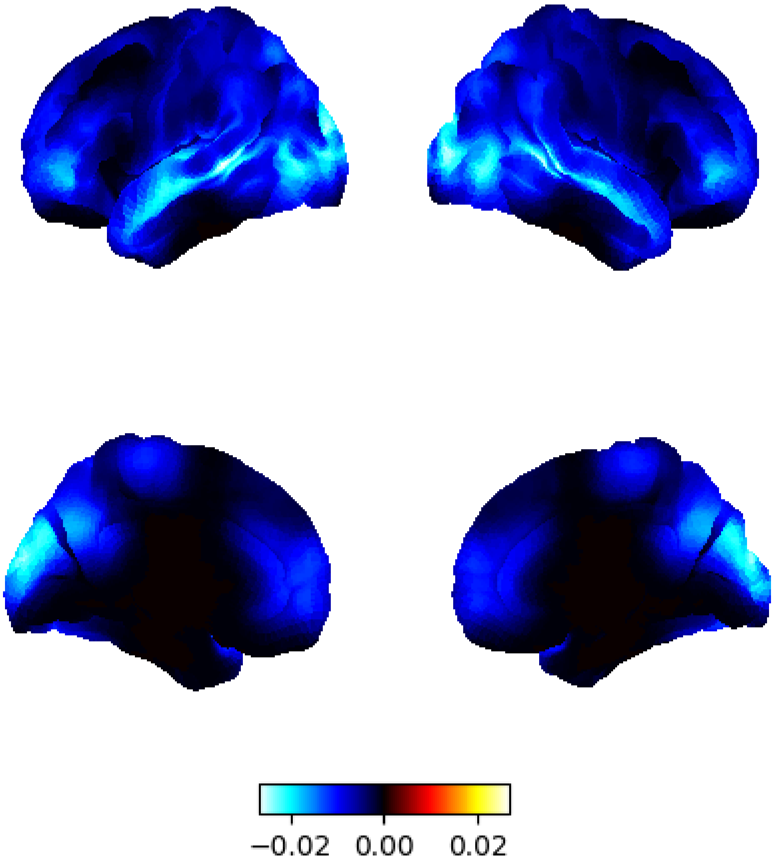
Plot **relative** to something else (by **substracting the mean**)

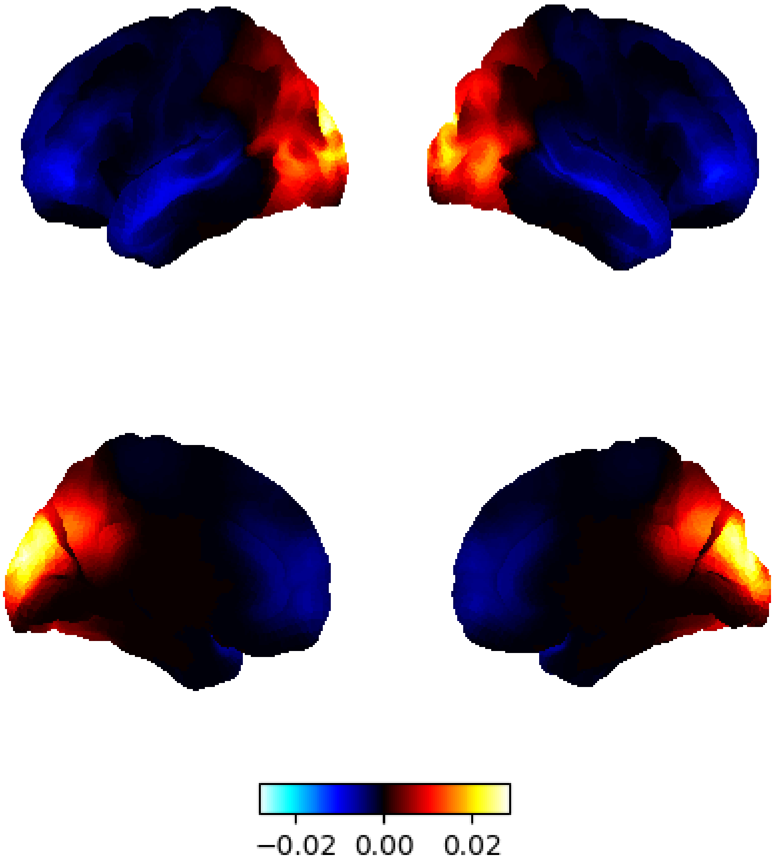
In [127…

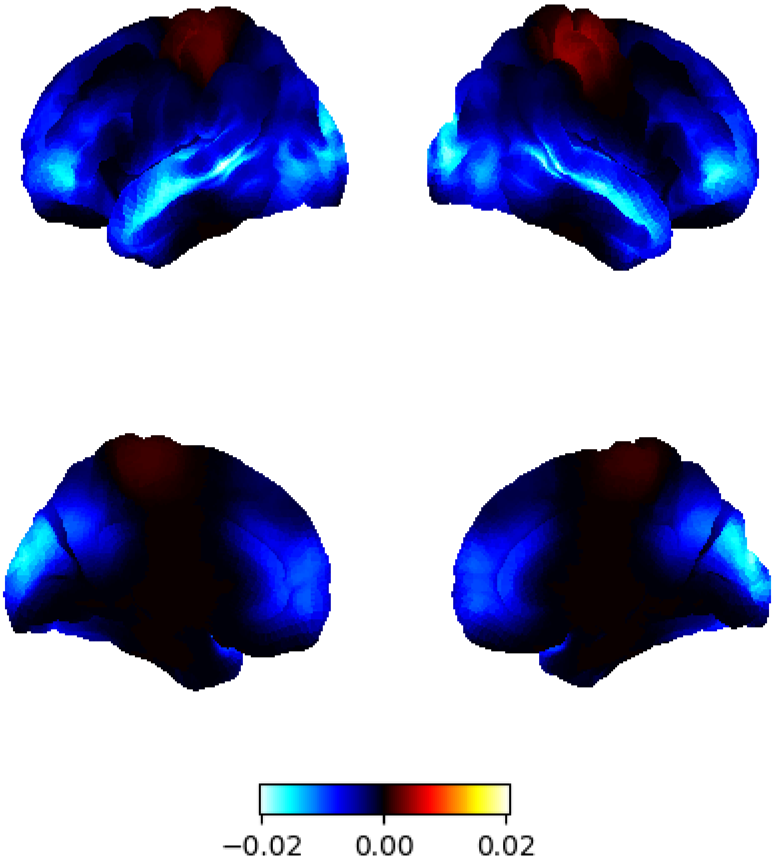
```
# Takes a few seconds for the power maps to appear
fig, ax = power.save(
    p_sc1,
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
    subtract_mean=True,
)
```

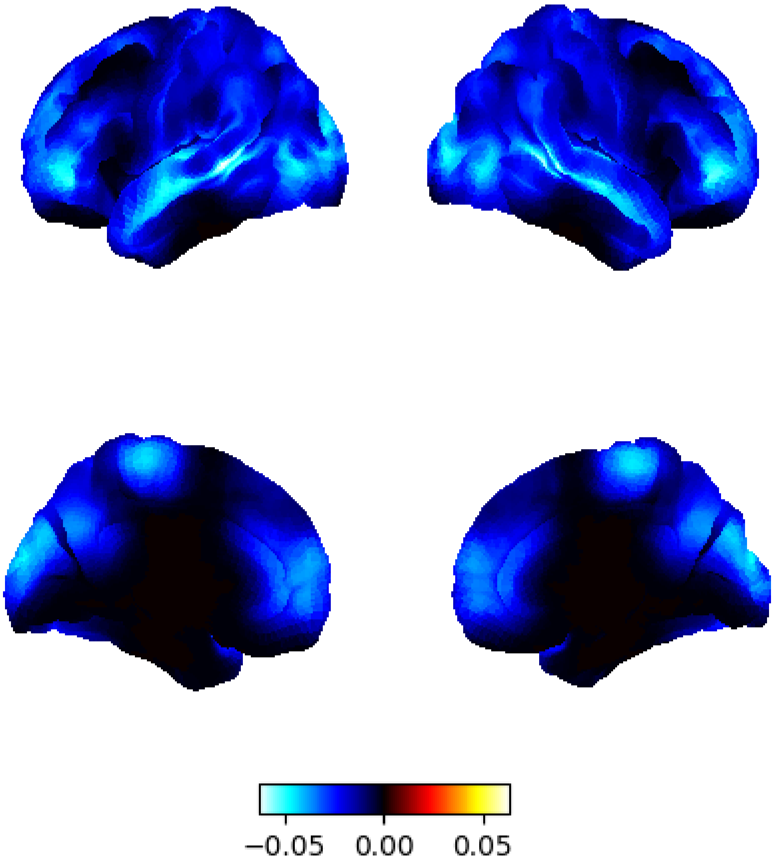
```
Saving images: 100%|██████████| 8/8 [00:08<00:00,  1.07s/it]
```

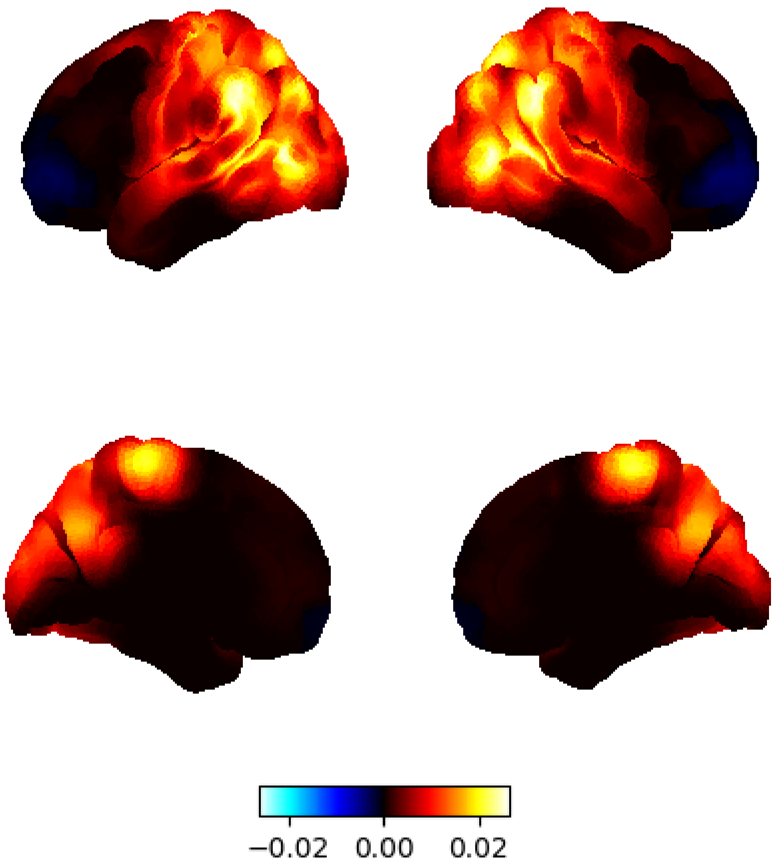

−0.01
0.00
0.01

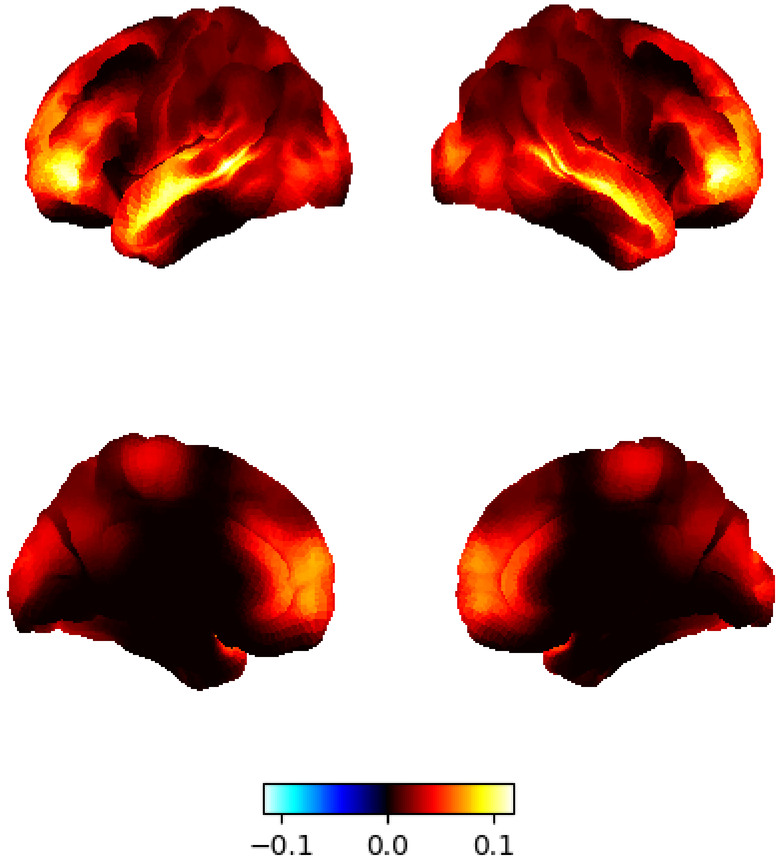

−0.02
0.00
0.02

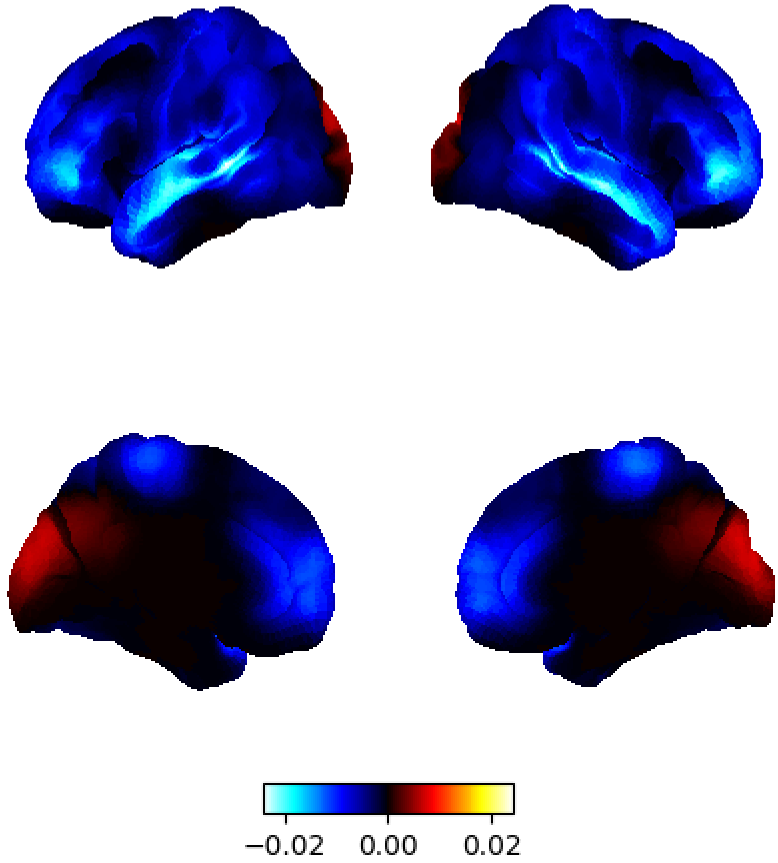

−0.02 0.00 0.02


−0.02 0.00 0.02


−0.05
0.00
0.05


−0.02
0.00
0.02



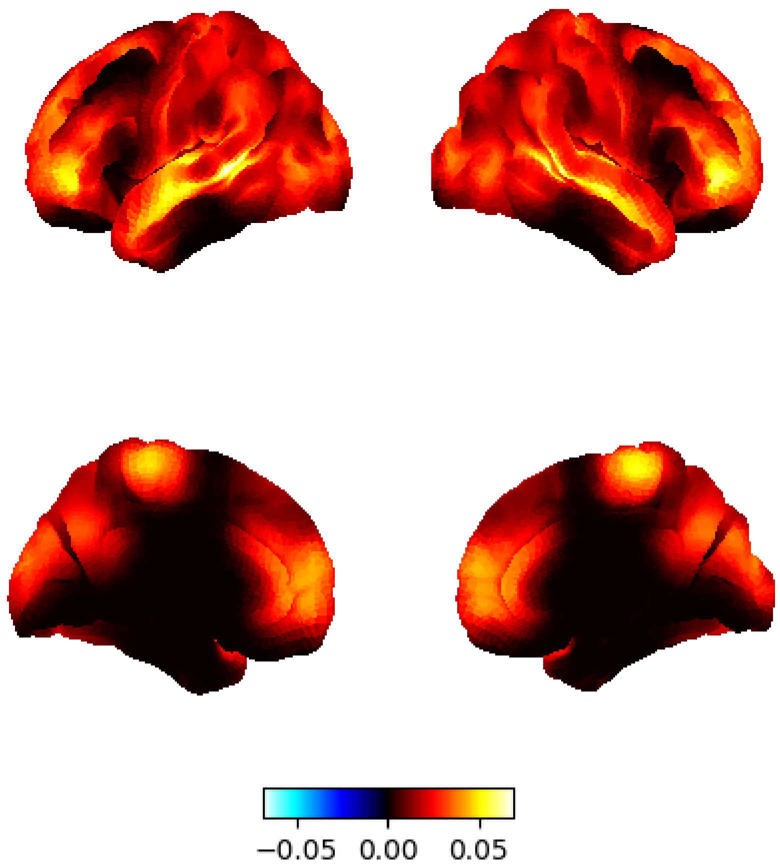


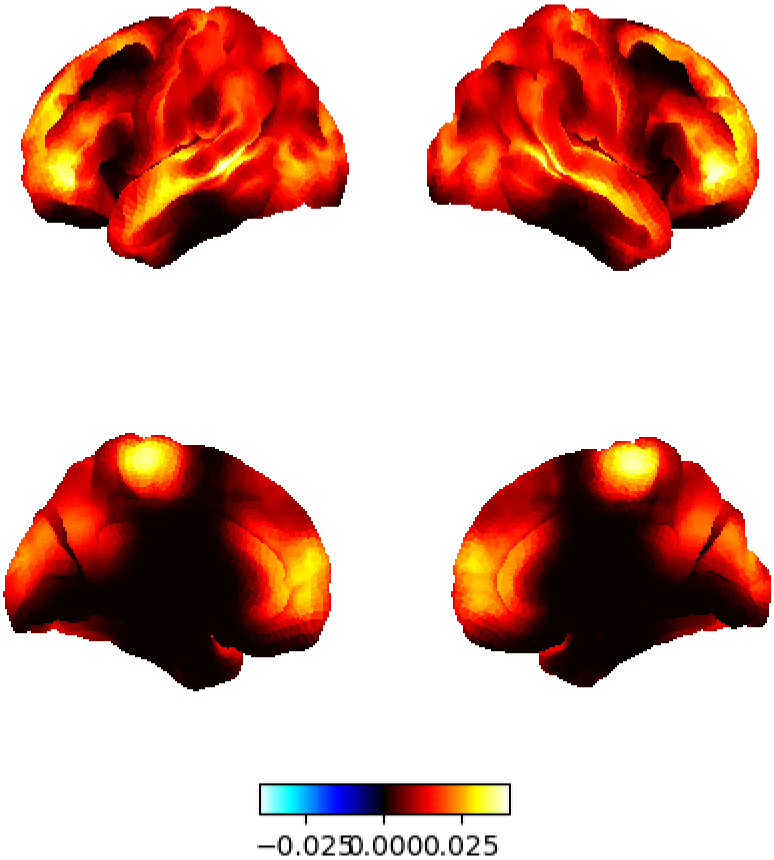
Group analysis

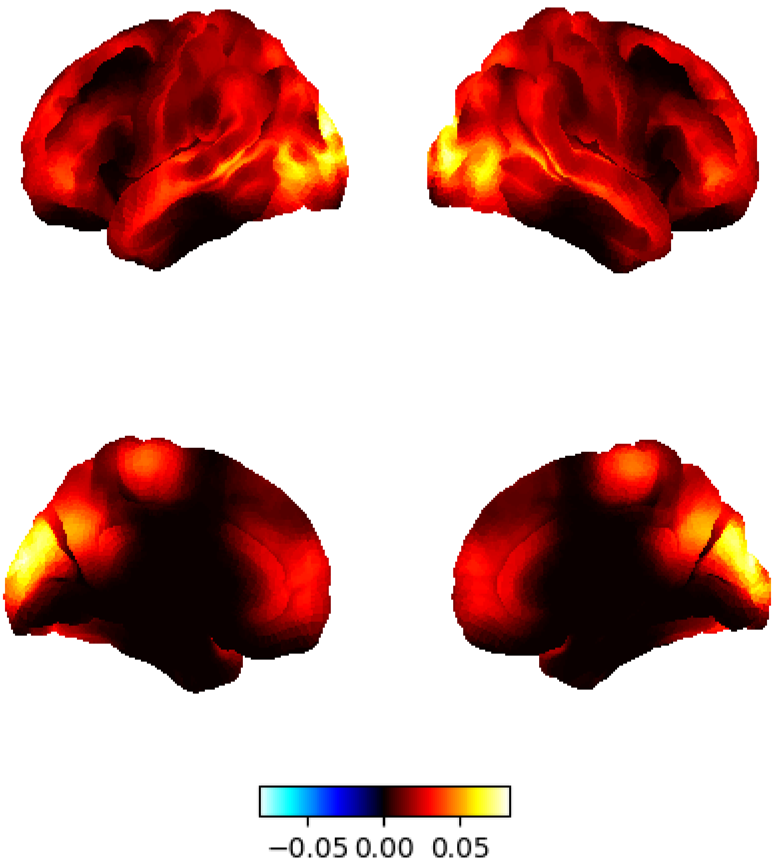
In [128…

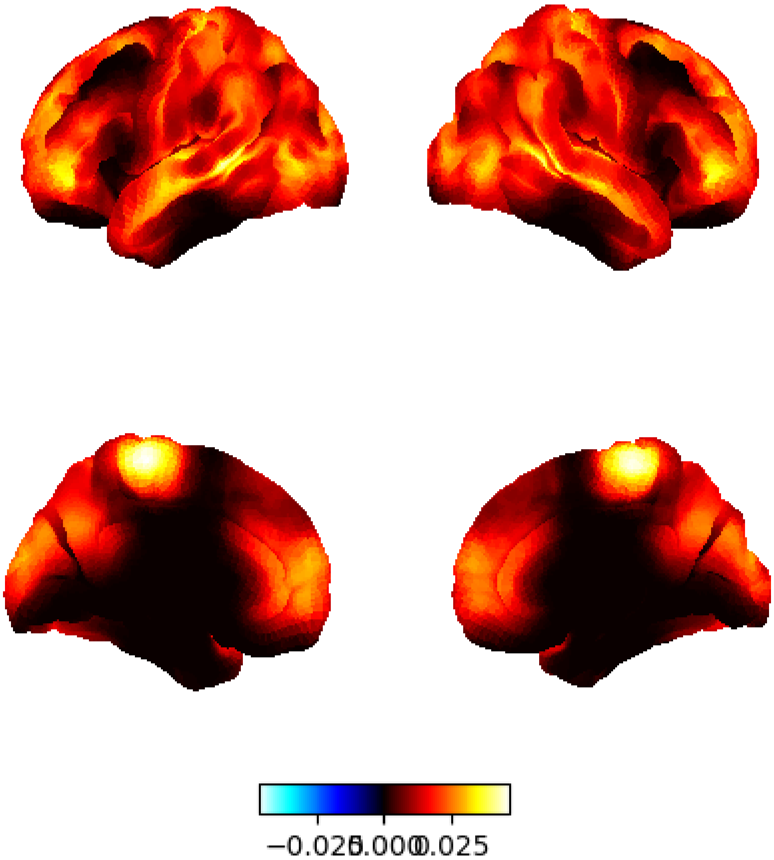
```
# Get the power arrays for group 1
p_sc1_control = power.variance_from_spectra(f, psd, wb_comp)[df_control_idx,

# Get the power arrays for group 2
p_sc1_ms = power.variance_from_spectra(f, psd, wb_comp)[df_ms_idx,0]

# Group means
p_sc1_control_mean = np.mean(p_sc1_control,axis=0)
p_sc1_ms_mean = np.mean(p_sc1_ms,axis=0)

print(np.shape(p_sc1_control))
print(np.shape(p_sc1_control_mean))

# Plot (it takes a few seconds for the brain maps to be shown)
fig, ax = power.save(
    [p_sc1_control_mean, p_sc1_ms_mean],
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
)
```

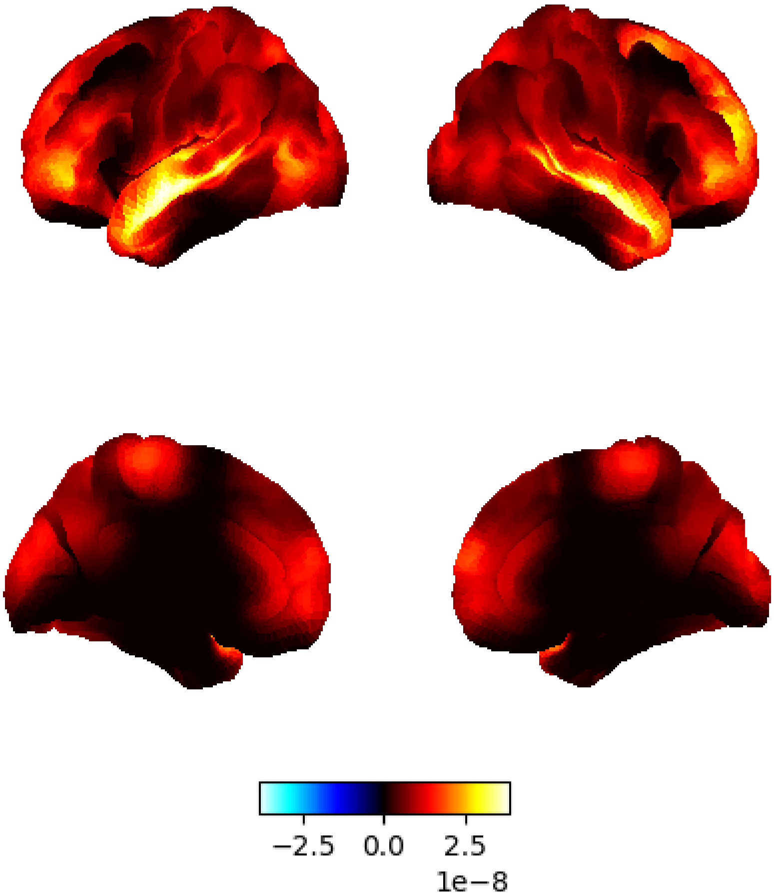
```
(37, 8, 38)
(8, 38)
Saving images: 100%|██████████| 8/8 [00:08<00:00,  1.12s/it]
```

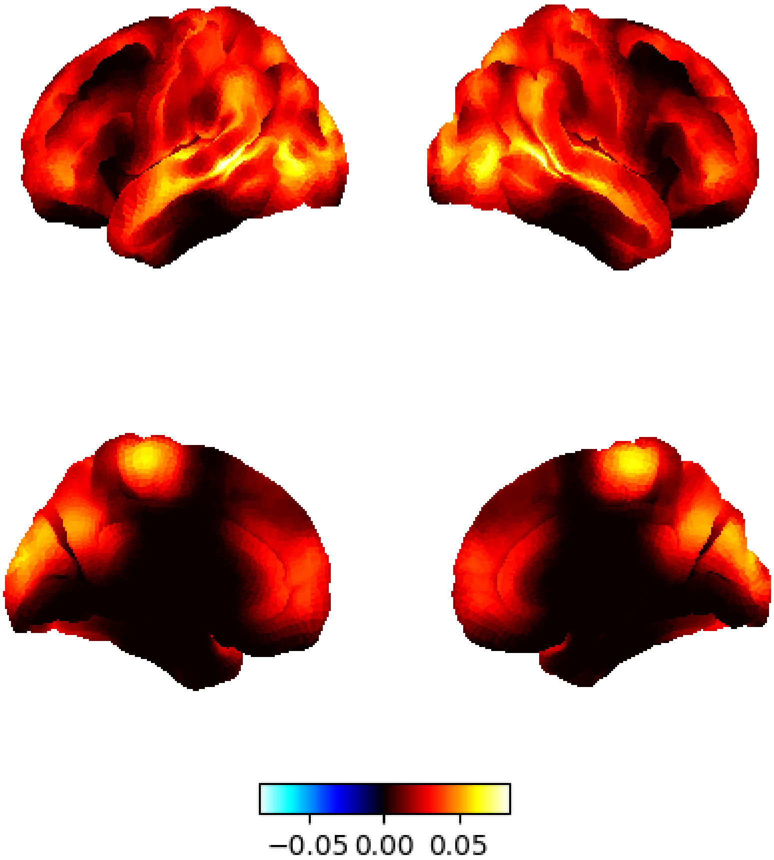


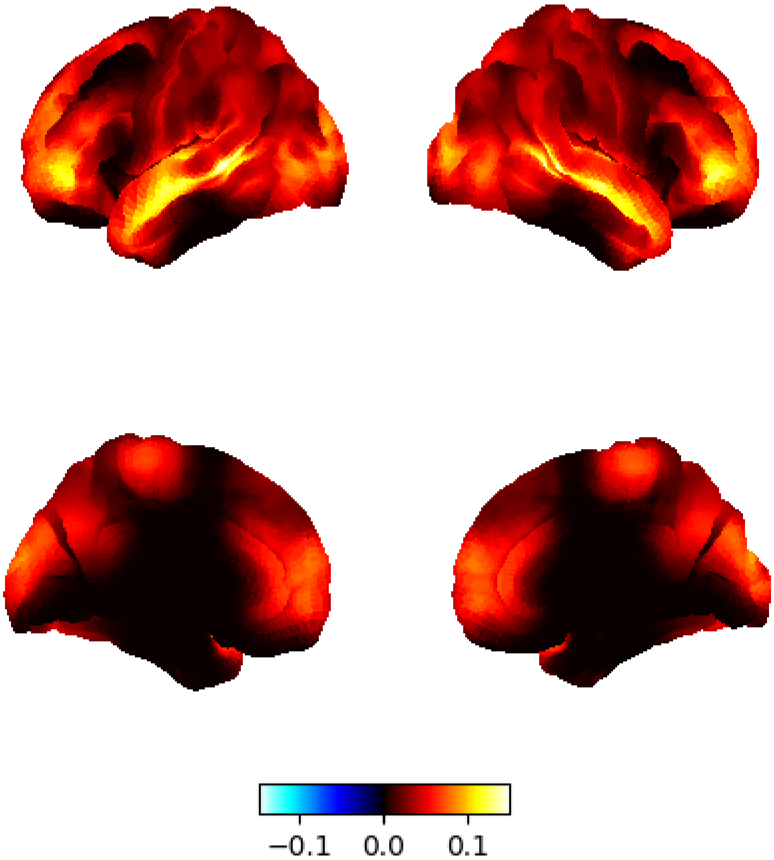

−0.0250.0000.025

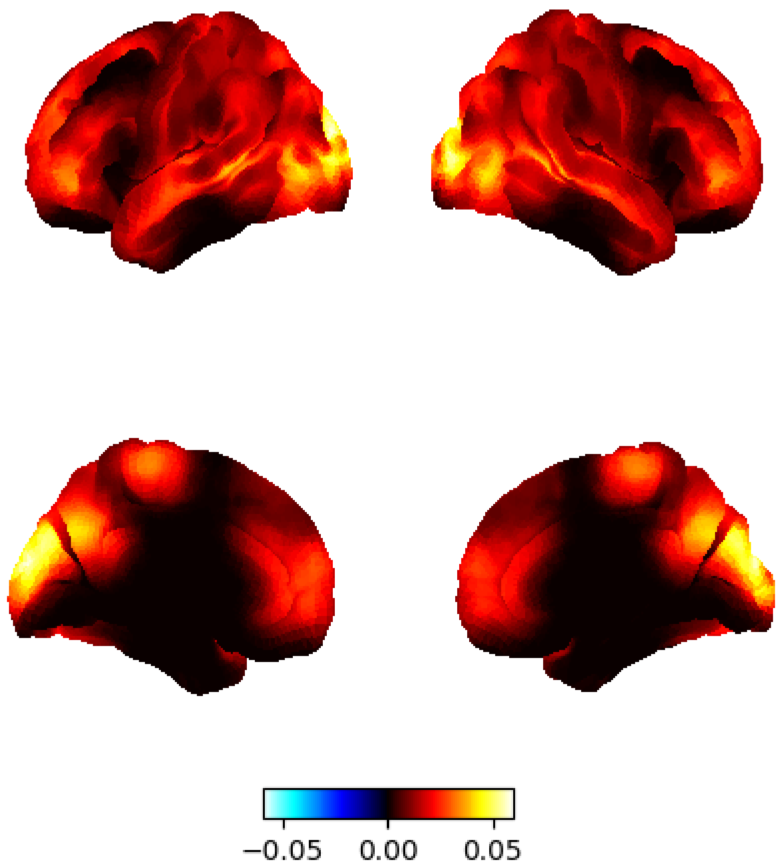

−0.05 0.00 0.05


−0.025
0.000
0.025


−2.5
0.0
2.5
1e−8


−0.05 0.00 0.05


−0.1 0.0 0.1

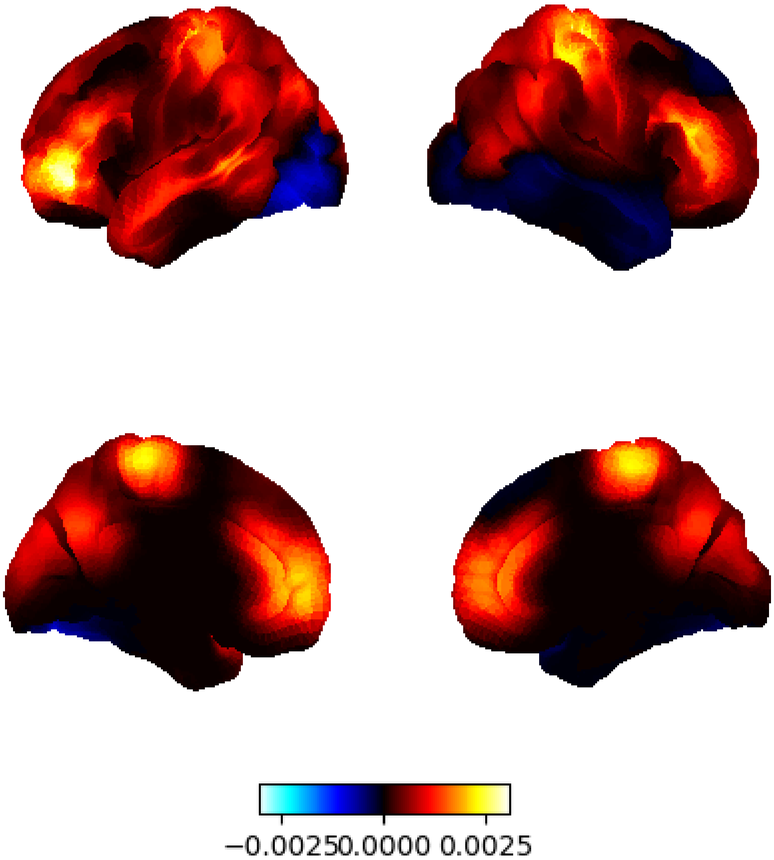


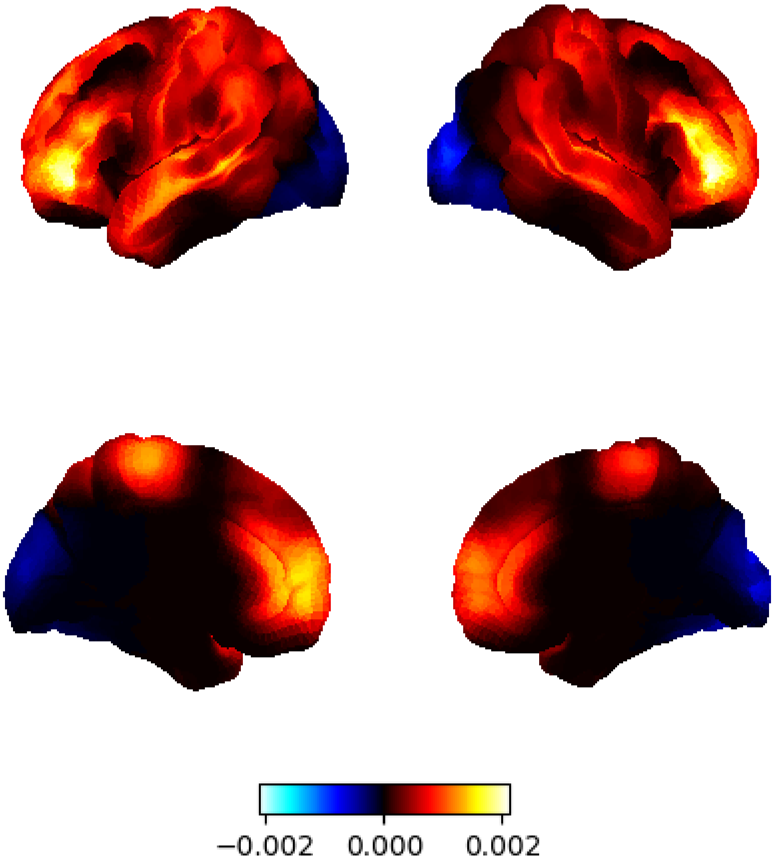
Plot the **diffference between the 2 groups**

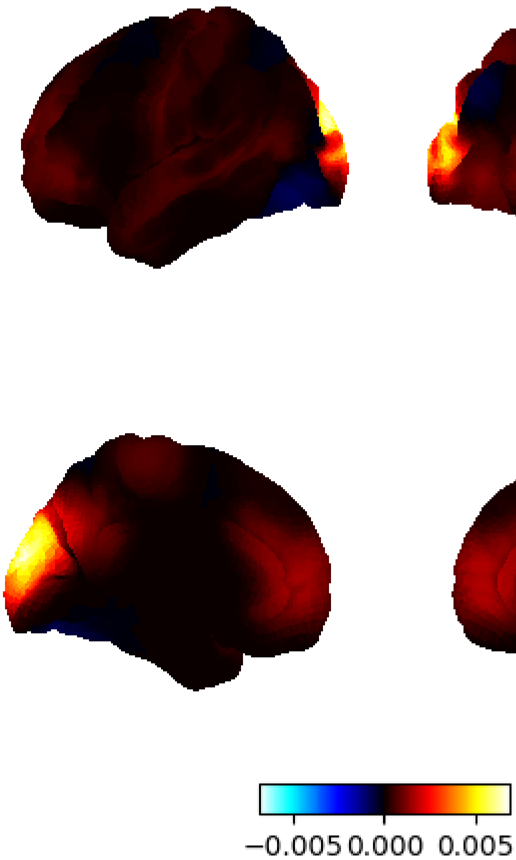
In [129…

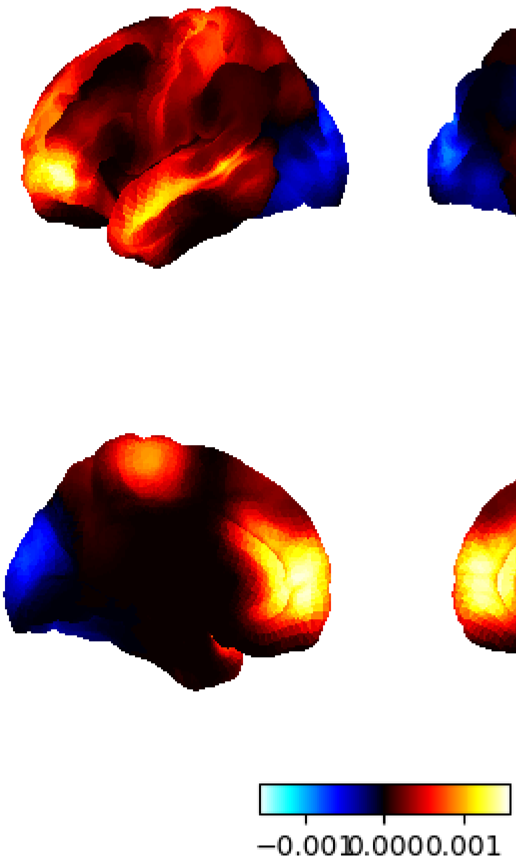
```
# Calculate the difference in power between the groups
p_diff = p_sc1_control_mean - p_sc1_ms_mean

# Plot
fig, ax = power.save(
    p_diff,
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
)
```

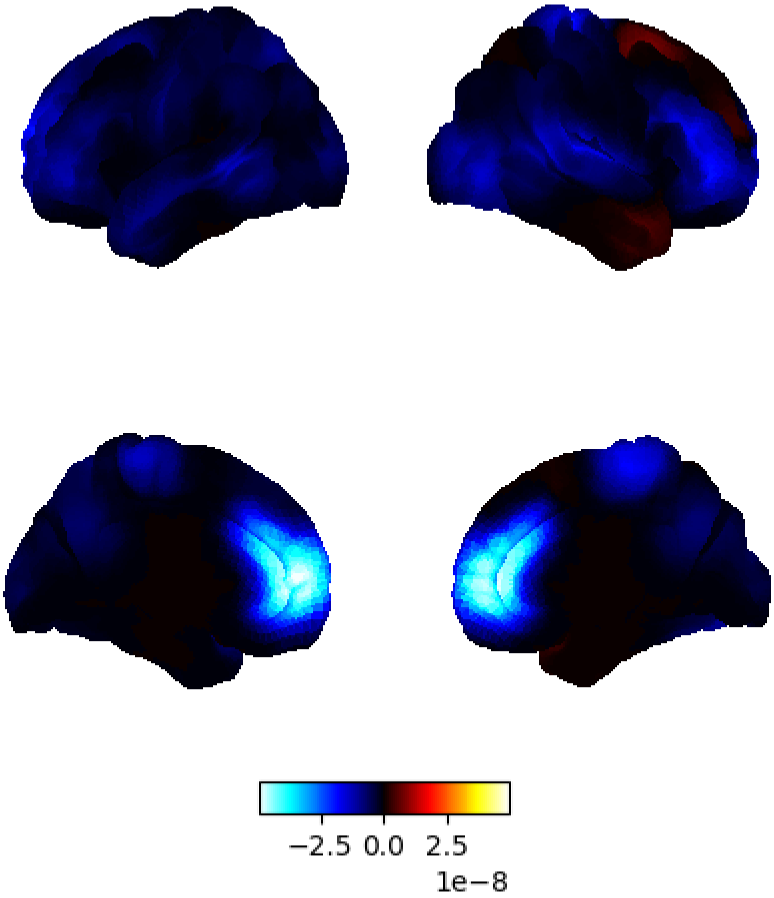
```
Saving images: 100%|██████████| 8/8 [00:08<00:00,  1.05s/it]
```

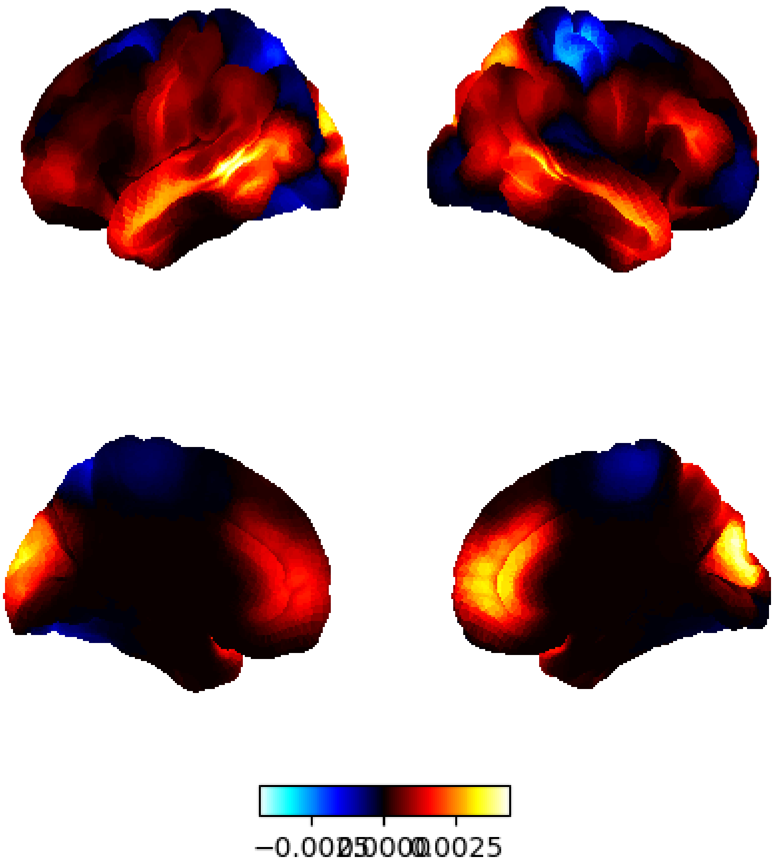

−0.00250.0000 0.0025

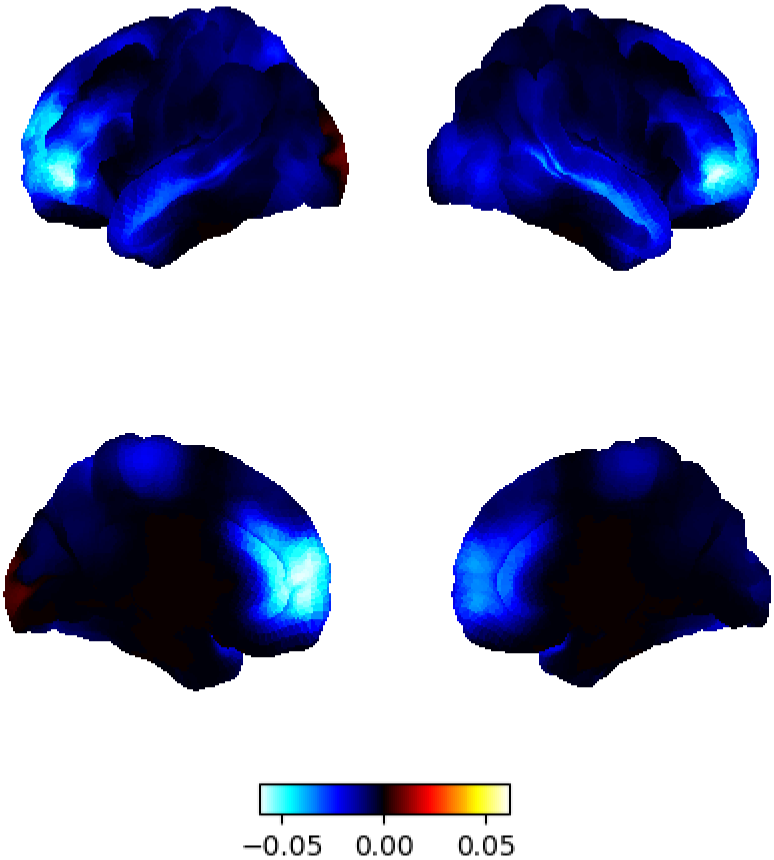

−0.002 0.000 0.002

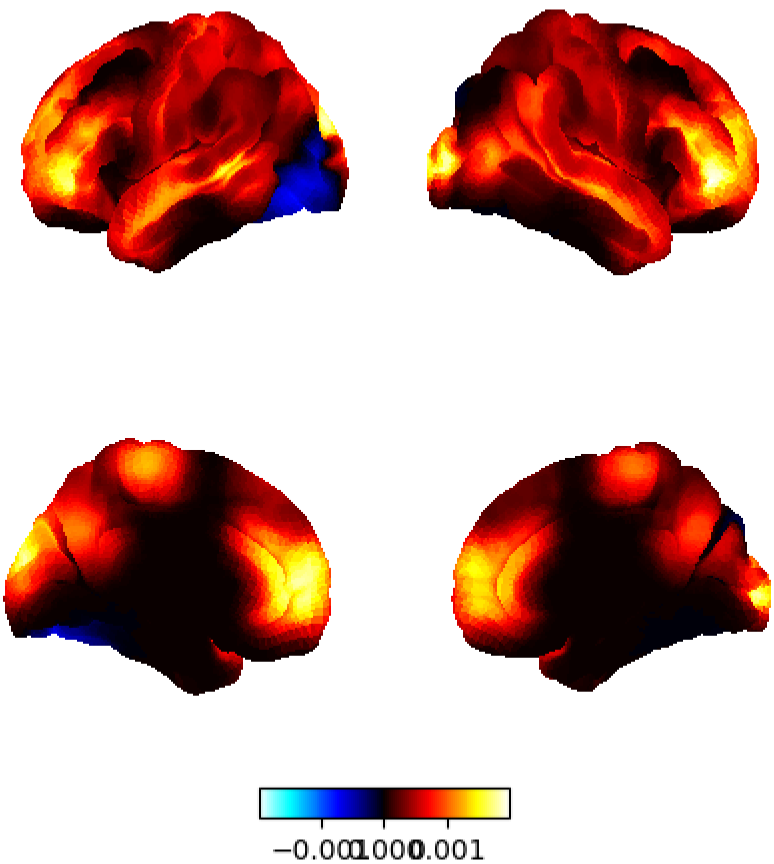

−0.005
0.000
0.005


−0.001
0.000
0.001


−2.5 0.0 2.5
1e−8


−0.0025 0.0000 0.0025





Statistical significance testing

HC vs. MS

In [131…

```
from osl_dynamics.analysis import statistics

# Group assignments
## use assignments variable defined in the section of the Summary Statistics
p_sc1_gd = power.variance_from_spectra(f, psd, wb_comp)[:,0]

# Do significant testing
diff, pvalues = statistics.group_diff_max_stat_perm(
    p_sc1_gd,
    assignments,
    n_perm=500,
)

# Do we have any significant parcels?
print("Number of significant parcels:", np.sum(pvalues < 0.05))
```

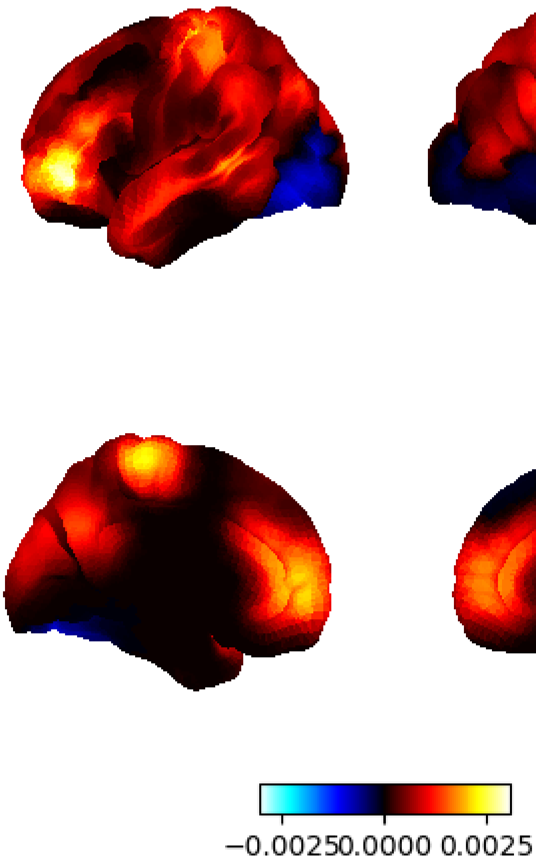
```
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Differentia
l) with mode=row-shuffle
        Computing 500 permutations
        Taking max-stat across ['features 1', 'features 2'] dimensions
Using tstats as metric
Number of significant parcels: 0
```

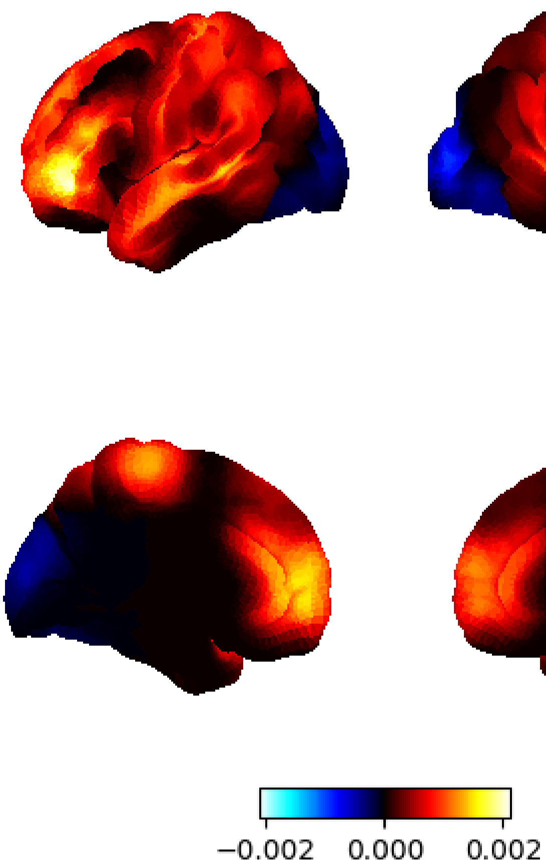
If you have parcels with a significant difference in power between groups:

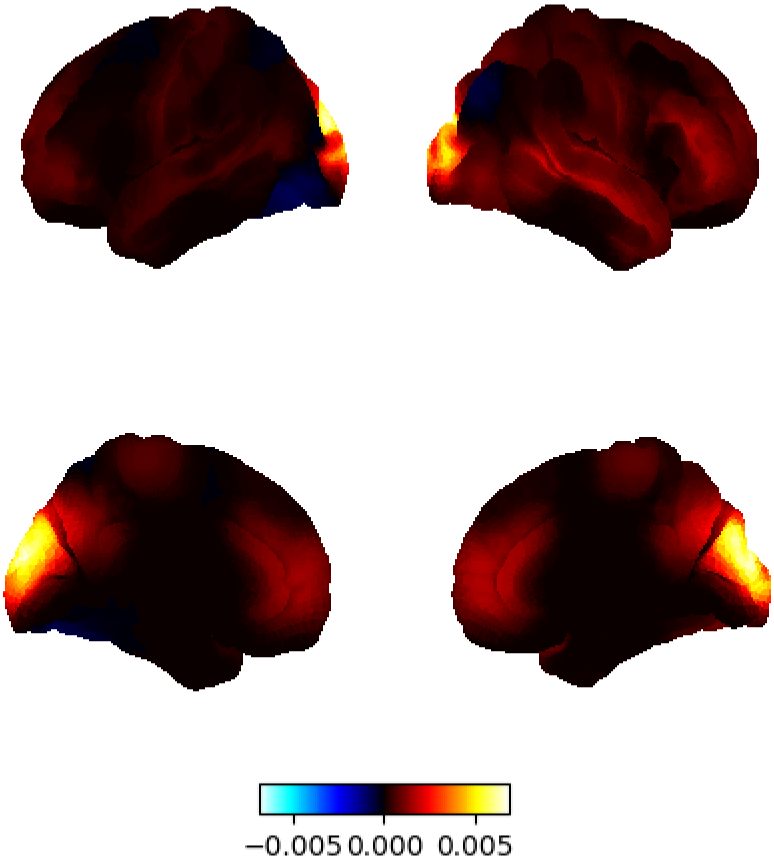
In [132…

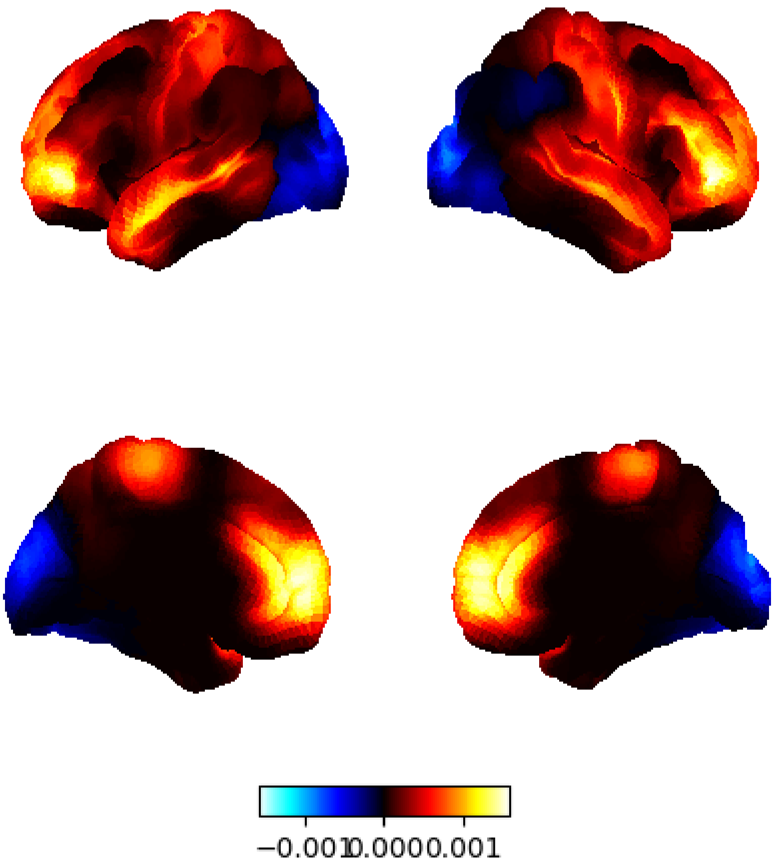
```
# Zero non-significant parcels
diff_sig = diff.copy()
diff_sig[pvalues < 0.05] = 0

# Plot
fig, ax = power.save(
    diff_sig,
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
)
```

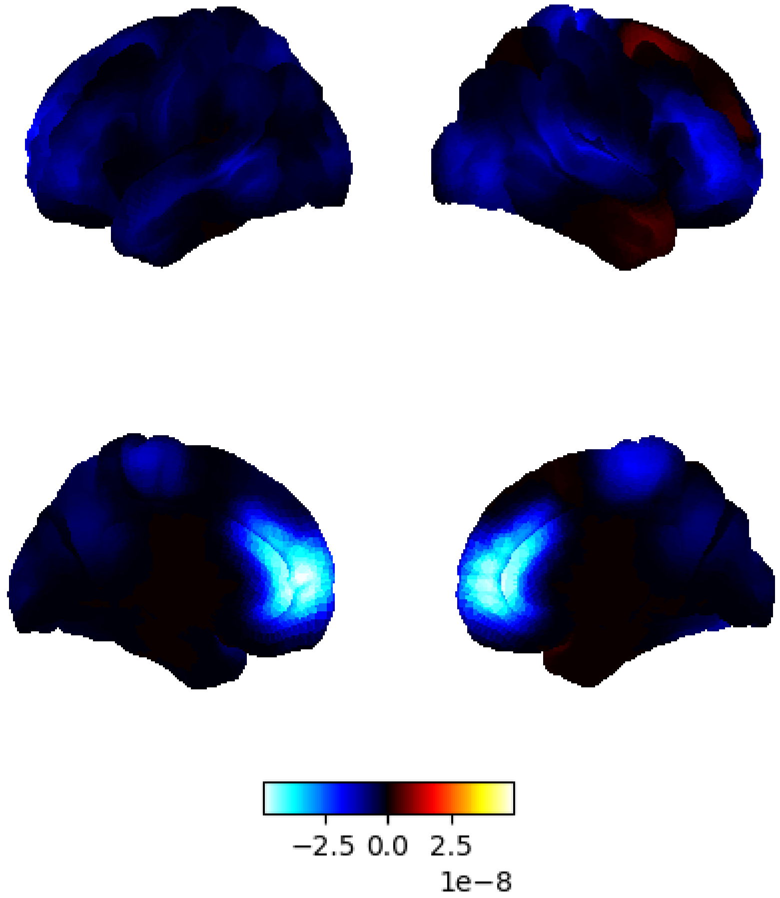
```
Saving images: 100%|██████████| 8/8 [00:08<00:00,  1.07s/it]
```

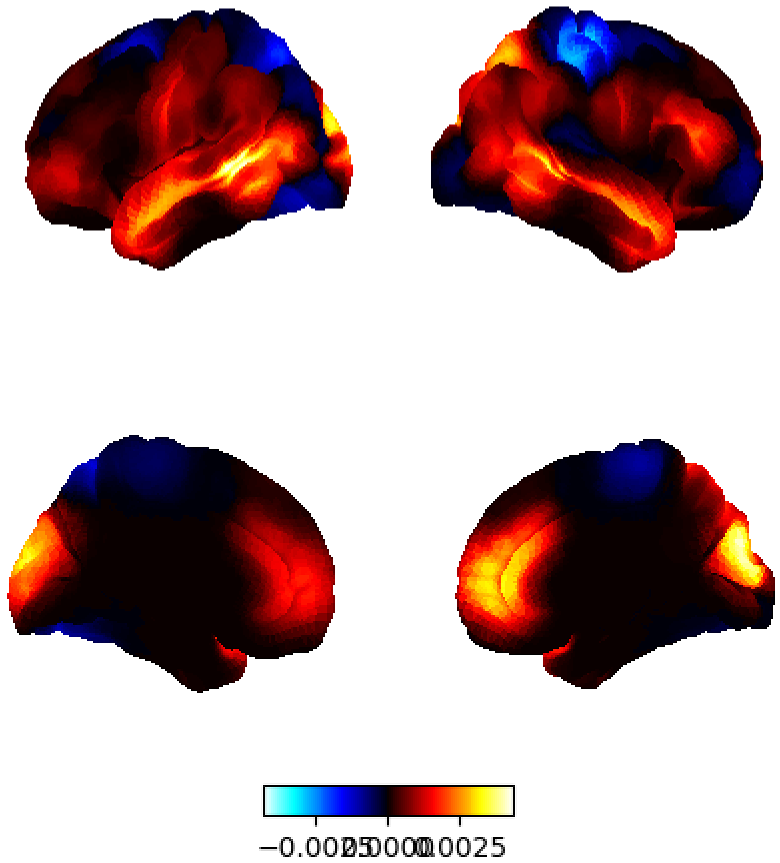

−0.0025
0.0000
0.0025

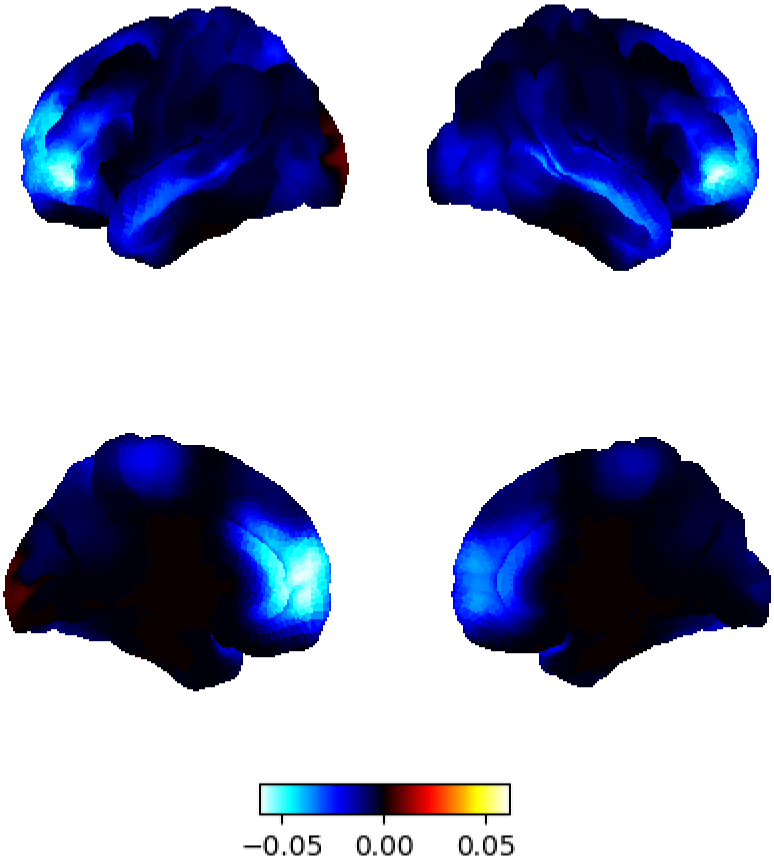

−0.002
0.000
0.002

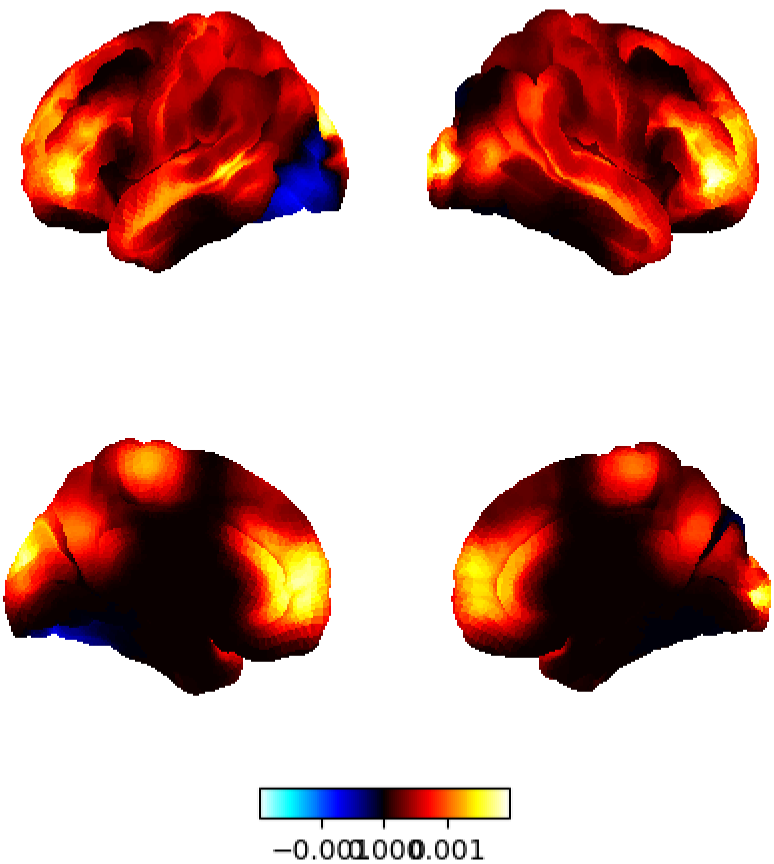

−0.005
0.000
0.005


−0.001
0.000
0.001


−2.5 0.0 2.5
1e−8


−0.0025 0.0000 0.0025





Coherence plots

NNMF

In [295…

```
# Calculate the coherence network for each state by weighting with the spect
c = connectivity.mean_coherence_from_spectra(f, coh, wb_comp)
print(c.shape)

# Average over subjects
mean_c = np.mean(c, axis=0)
print(mean_c.shape)

# Threshold each network and look for the top 3% of connections relative to
thres_mean_c = connectivity.threshold(mean_c, percentile=98, subtract_mean=T
print(thres_mean_c.shape)
```

```
(110, 4, 8, 38, 38)
(4, 8, 38, 38)
(4, 8, 38, 38)
```

In [296…

```
sc = 0
os.makedirs(model_name + "/data/Images" + "/Basic_Coherence_NNMF", exist_ok=
connectivity.save(
    thres_mean_c,
    parcellation_file="/home/olivierb/38_parcels.nii",
    component=sc, #1st spectral component
    filename=model_name + "/data/Images/Basic_Coherence_NNMF/coh_Spectral_Co
)
```

```
Saving images: 100%|██████████| 8/8 [00:11<00:00,  1.48s/it]
```

In [135…

```
connectivity_6states_SC1 = thres_mean_c[0]
connectivity_6states_SC1_S1 = connectivity_6states_SC1[0]

print(connectivity_6states_SC1_S1)
```

```
[[0.9999999 0.         0.         ... 0.         0.         0.        ]
 [0.        0.         0.         ... 0.         0.         0.        ]
 [0.        0.         0.         ... 0.         0.         0.        ]
 ...
 [0.        0.         0.         ... 0.         0.         0.        ]
 [0.        0.         0.         ... 0.         0.         0.        ]
 [0.        0.         0.         ... 0.         0.         0.        ]]
```

Get locations of parcel-centers for the 38 parcel data

In [136…

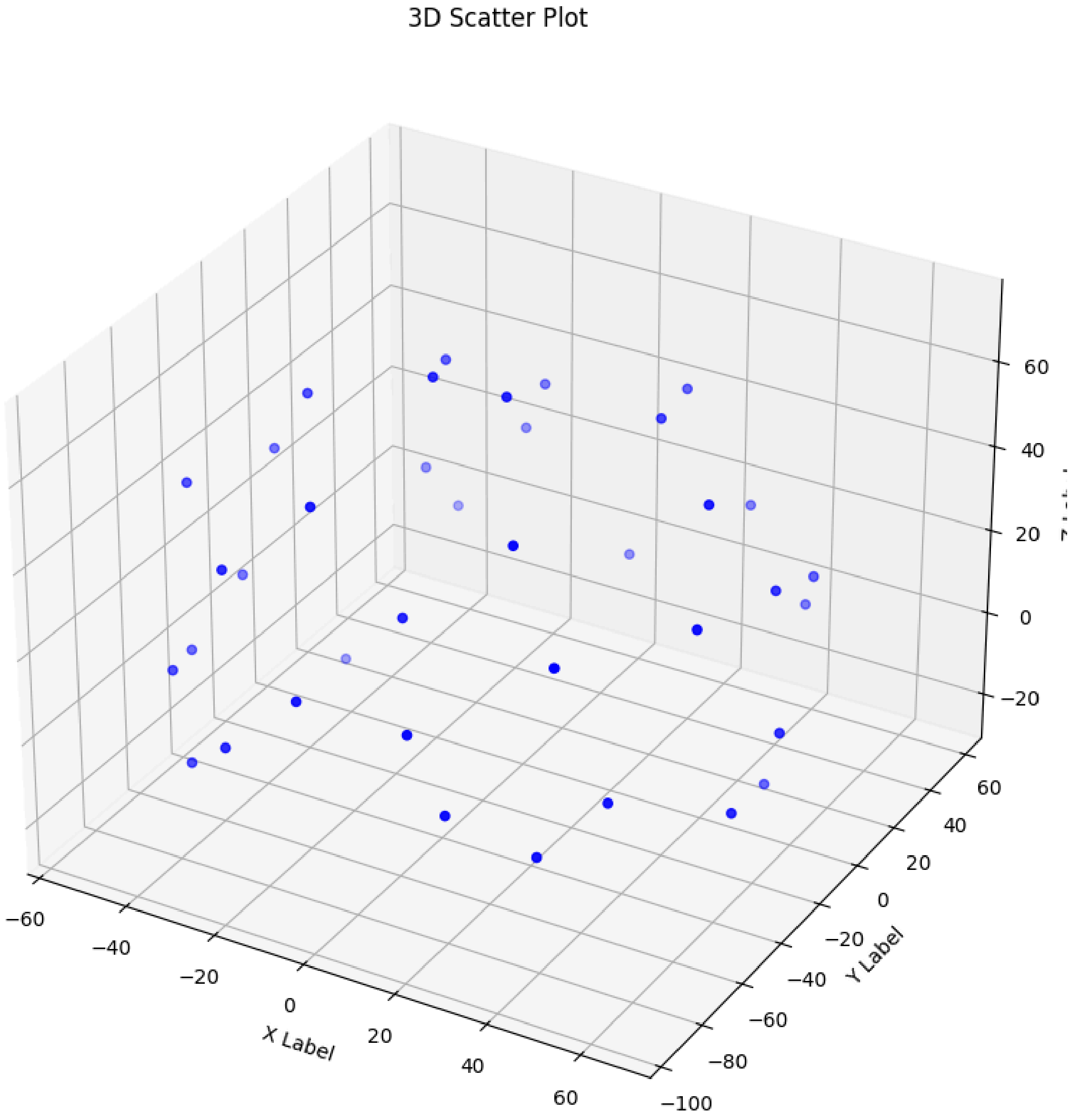
```
import nibabel as nib
from nilearn import image, plotting
path_parcel = "/home/olivierb/38_parcels.nii"
nii_img = image.load_img(path_parcel)

# Get the coordinates of all voxels in realistic 3D space
shape = nii_img.shape

# Create a grid of voxel coordinates
x, y, z = np.meshgrid(range(shape[0]), range(shape[1]), range(shape[2]), inc

# Stack the voxel coordinates into a single array
voxel_coords = np.column_stack((x.ravel(), y.ravel(), z.ravel()))

# Get the affine matrix
affine = nii_img.affine

world_coords = nib.affines.apply_affine(affine, voxel_coords)
```

```
x_min, x_max = np.min(world_coords[:,0]), np.max(world_coords[:,0])
y_min, y_max = np.min(world_coords[:,1]), np.max(world_coords[:,1])
z_min, z_max = np.min(world_coords[:,2]), np.max(world_coords[:,2])

x_axis = np.arange(x_min, x_max+8, 8)
y_axis = np.arange(y_min, y_max+8, 8)
z_axis = np.arange(z_min, z_max+8, 8)

parcel_centers = []

n_parcels = np.shape(nii_img)[3]
for i in range(n_parcels):
    one_volume_data = image.index_img(nii_img, i).get_fdata()
    location_center = np.where(one_volume_data == np.max(one_volume_data))
    loc = [location_center[axis][0] for axis in range(3)]
    loc_space = [x_axis[loc[0]], y_axis[loc[1]], z_axis[loc[2]]]
    parcel_centers.append(loc_space)

print(parcel_centers)
```

```
[[18.0, -94.0, 24.0], [-6.0, -94.0, 24.0], [42.0, -86.0, 0.0], [-38.0, -7
8.0, -8.0], [58.0, -6.0, 32.0], [-54.0, -6.0, 32.0], [66.0, -22.0, 8.0],
[-54.0, -22.0, 8.0], [50.0, -22.0, 56.0], [-38.0, -22.0, 56.0], [26.0, -6
2.0, 56.0], [-14.0, -70.0, 56.0], [50.0, -70.0, 8.0], [-46.0, -70.0, 8.
0], [42.0, -78.0, 40.0], [-30.0, -78.0, 40.0], [50.0, 10.0, -24.0], [-46.
0, 10.0, -24.0], [10.0, -30.0, 72.0], [-6.0, -30.0, 72.0], [58.0, -46.0,
40.0], [-54.0, -46.0, 40.0], [50.0, 34.0, 16.0], [-38.0, 34.0, 16.0], [2
6.0, -94.0, 8.0], [-22.0, -94.0, 8.0], [26.0, 10.0, 56.0], [-22.0, 10.0,
56.0], [18.0, 42.0, 48.0], [-14.0, 42.0, 40.0], [42.0, 50.0, 0.0], [-38.
0, 50.0, 0.0], [66.0, -46.0, 0.0], [-54.0, -46.0, 0.0], [26.0, 58.0, 16.
0], [-22.0, 50.0, 24.0], [2.0, -62.0, 32.0], [2.0, 50.0, 0.0]]
```

In [137…

```
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D  # Import the 3D plotting toolkit

# Extract X, Y, and Z coordinates from the array
x = [parcel_centers[parcel][0] for parcel in range(len(parcel_centers))]
y = [parcel_centers[parcel][1] for parcel in range(len(parcel_centers))]
z = [parcel_centers[parcel][2] for parcel in range(len(parcel_centers))]

# Create a 3D scatter plot
fig = plt.figure(figsize=(10,10))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(x, y, z, c='b', marker='o')  # 'c' sets the color, 'marker' defir

# Set axis labels
ax.set_xlabel('X Label')
ax.set_ylabel('Y Label')
ax.set_zlabel('Z Label')

plt.title('3D Scatter Plot')
plt.show()
```



In [138…

```
import numpy as np
import matplotlib.pyplot as plt
from IPython import display

import mne
from mne.datasets import sample
from mne.minimum_norm import apply_inverse_epochs, read_inverse_operator
from mne.viz import circular_layout
from mne_connectivity import spectral_connectivity_epochs
from mne_connectivity.viz import plot_connectivity_circle

import numpy as np

from osl_dynamics.analysis import connectivity
```

In [210…

```
# Adapted from: https://mne.tools/mne-connectivity/stable/auto_examples/mne_
def plot_spatial_map_connectivity(connectivity_matrix, parcel_names, percent

    ##### PLOT Circular graph

    ###  Throw except if shape mismatch between connectivity matrix & amount
    if np.shape(connectivity_matrix) != (len(parcel_names), len(parcel_names
        raise ValueError("Connectivity matrix shape must have same shape as

    label_names = parcel_names
```

```
    ## Add a way to go from the back to the front of the brain (in the order
    # without the 2 non-symmetric parcels
    lh_idx = np.arange(0,38,2)
    rh_idx = np.arange(1,39,2)

    sorted_indices_lh = lh_idx[np.argsort(np.array(y)[lh_idx])]
    sorted_indices_rh = rh_idx[np.argsort(np.array(y)[rh_idx])]

    lh_labels = []
    rh_labels = []

    # Reorder the labels based on their location
    lh_labels = [label_names[i] for i in sorted_indices_lh]
    rh_labels = [label_names[i] for i in sorted_indices_rh]

    # Add the 2 extra parcels
    #lh_labels.append(label_names[36])
    #rh_labels.append(label_names[37])

    # Save the plot order and create a circular layout
    ## Double-checked to make sure that changing anything in the order here

    node_order = []
    node_order.extend(lh_labels[::-1])
    node_order.extend(rh_labels)


    node_angles = circular_layout(label_names, node_order, start_pos=90,
                                  group_boundaries=[0, len(label_names) / 2]

    # Plot the graph using node colors from the FreeSurfer parcellation. We
    # show the 300 strongest connections.
    fig, ax = plt.subplots(figsize=(10, 10), facecolor='white',   # this col
                           subplot_kw=dict(polar=True))

    # Take a % of all strongest connections
    n_lines = 0
    if network:

        if plot_type == 'threshold':
        ###################################################################
        ## IF Percentile Thresholding
        ###################################################################
            n_lines = int((100-percentile)/100*len(label_names)*(len(label_n

        if plot_type == 'GMM':
        ###################################################################
        ## IF GMM Thresholding
        ###################################################################
            n_lines = int(((0 < connectivity_matrix) & (connectivity_matrix

            connectivity_matrix = np.array([[0 if element == 1.0000001 else

        plot_connectivity_circle(connectivity_matrix, label_names, n_lines=n
                                 node_angles=node_angles, title=title, ax=ax
                                 facecolor='white', textcolor='black', fonts
                                 fontsize_title=16, padding=7, node_edgecolo
                                 colorbar_size=0.5, colorbar_pos=(-0.3,0.5),

    return
```

In [140…

```
## Parcel names extract
```

```
# Open the .txt file for reading
file_path = "/home/olivierb/Downloads/Parcels_38_names.txt"
with open(file_path, 'r') as file:
    lines = file.readlines()

# Strip any leading/trailing whitespace and create a list of strings
parcel_names = [line.strip() for line in lines]

# Print the list of strings
print(parcel_names)

## Parcel indices (how the channel names are stored in the Python parceled .
parcel_idx= []
for i in range(len(parcel_names)):        # 38 parcels
    parcel_idx.append('parcel_' + str(i))
print(parcel_idx)
```

```
['L Cuneus', 'R Cuneus', 'L Inf Occ', 'R Inf Occ', 'L Supramarginal', 'R
Supramarginal', 'L Sup Temp', 'R Sup Temp', 'L Lat SMC', 'R Lat SMC', 'L
Sup Parietal', 'R Sup Parietal', 'L Middle Occ', 'R Middle Occ', 'L Sup O
cc', 'R Sup Occ', 'L Ant Temp', 'R Ant Temp', 'L Medial SMC', 'R Medial S
MC', 'L Angular', 'R Angular', 'L VL PFC', 'R VL PFC', 'L Occ pole', 'R O
cc pole', 'L Sup PFC', 'R Sup PFC', 'L Sup Dorsal PFC', 'R Sup Dorsal PF
C', 'L Orbitofrontal', 'R Orbitofrontal', 'L Post Temp', 'R Post Temp',
'L Inf Dorsal PFC', 'R Inf Dorsal PFC', 'Medial PFC', 'Posterior Cingulat
e Cortex']
['parcel_0', 'parcel_1', 'parcel_2', 'parcel_3', 'parcel_4', 'parcel_5',
'parcel_6', 'parcel_7', 'parcel_8', 'parcel_9', 'parcel_10', 'parcel_11',
'parcel_12', 'parcel_13', 'parcel_14', 'parcel_15', 'parcel_16', 'parcel_
17', 'parcel_18', 'parcel_19', 'parcel_20', 'parcel_21', 'parcel_22', 'pa
rcel_23', 'parcel_24', 'parcel_25', 'parcel_26', 'parcel_27', 'parcel_2
8', 'parcel_29', 'parcel_30', 'parcel_31', 'parcel_32', 'parcel_33', 'par
cel_34', 'parcel_35', 'parcel_36', 'parcel_37']
```

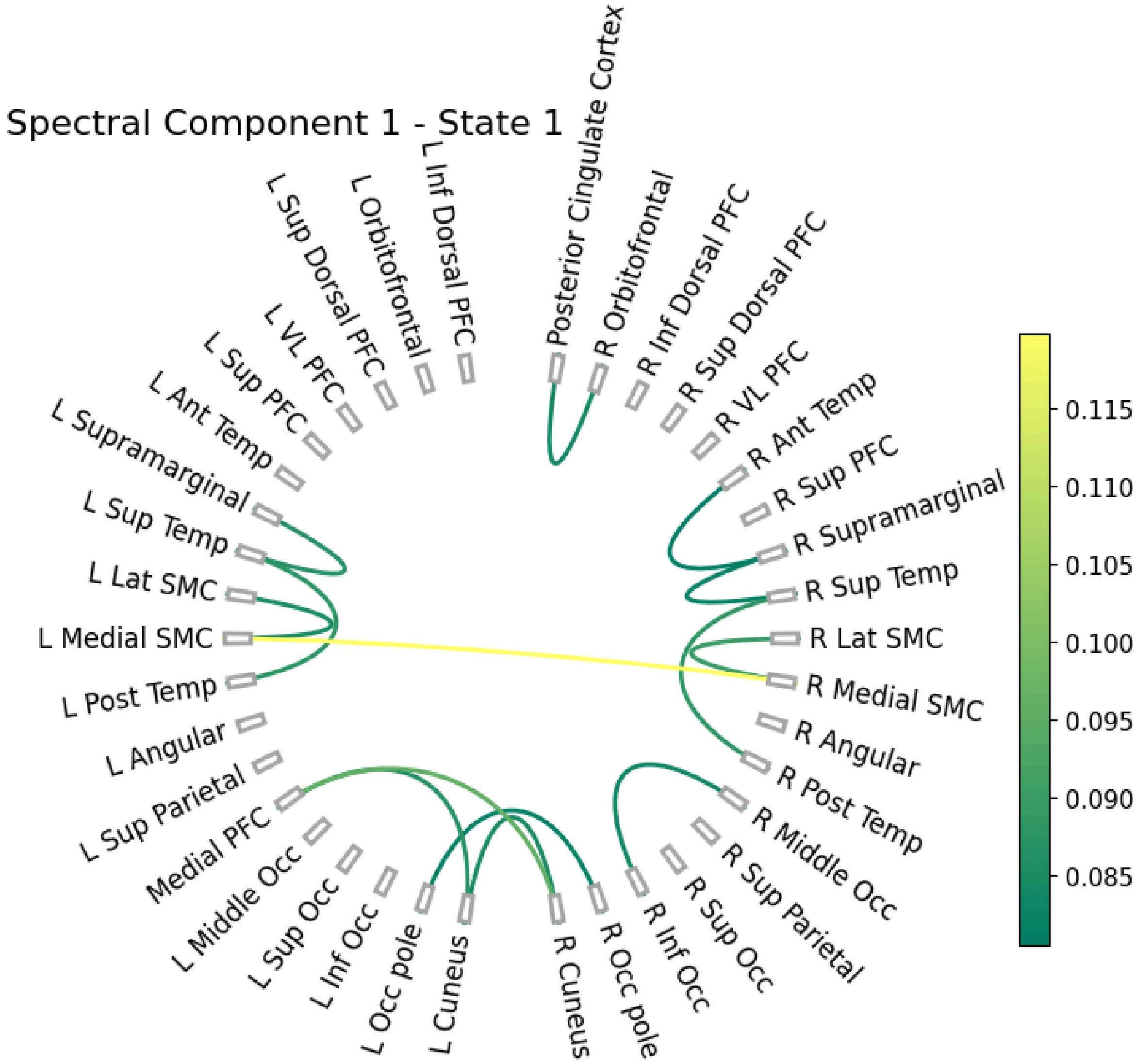
In [141…

```
#connectivity_6states_SC1_S1
```

Thresholded 2%

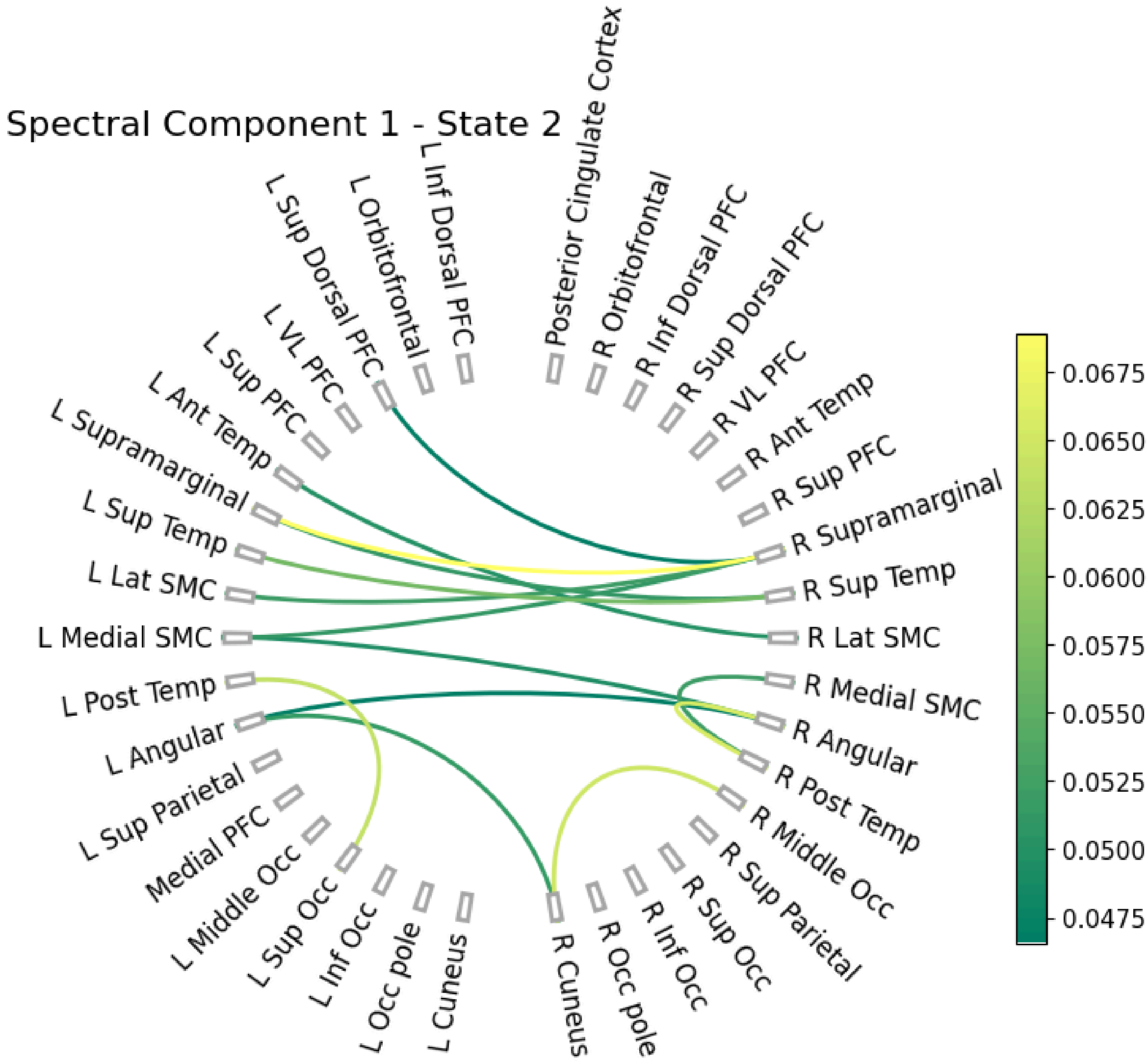
In [211…

```
sc=0
title = 'Spectral Component 1 - State 1
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



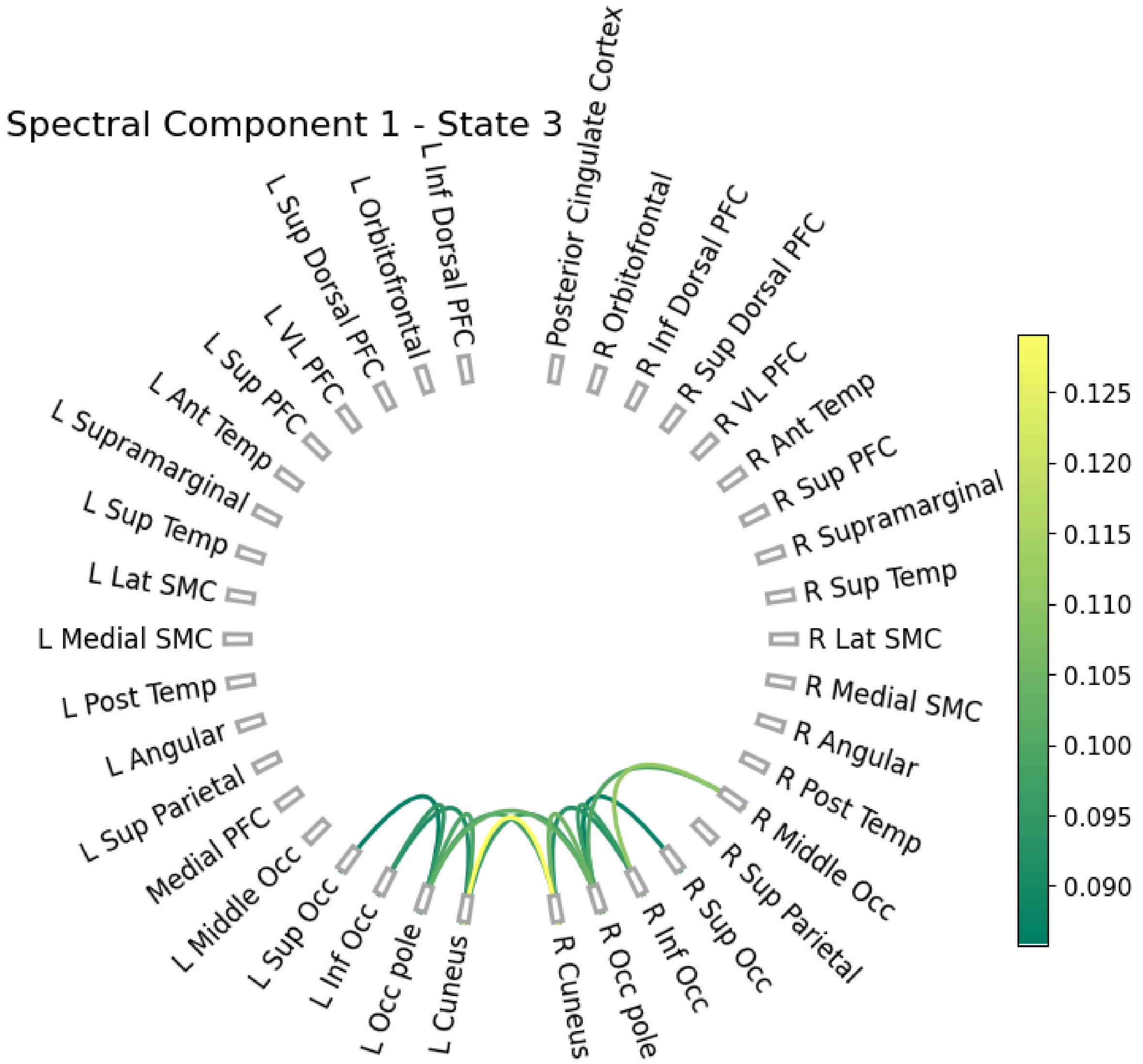
In [212…

```
connectivity_6states_SC1_S2 = connectivity_6states_SC1[1]

sc=0
title = 'Spectral Component 1 - State 2
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



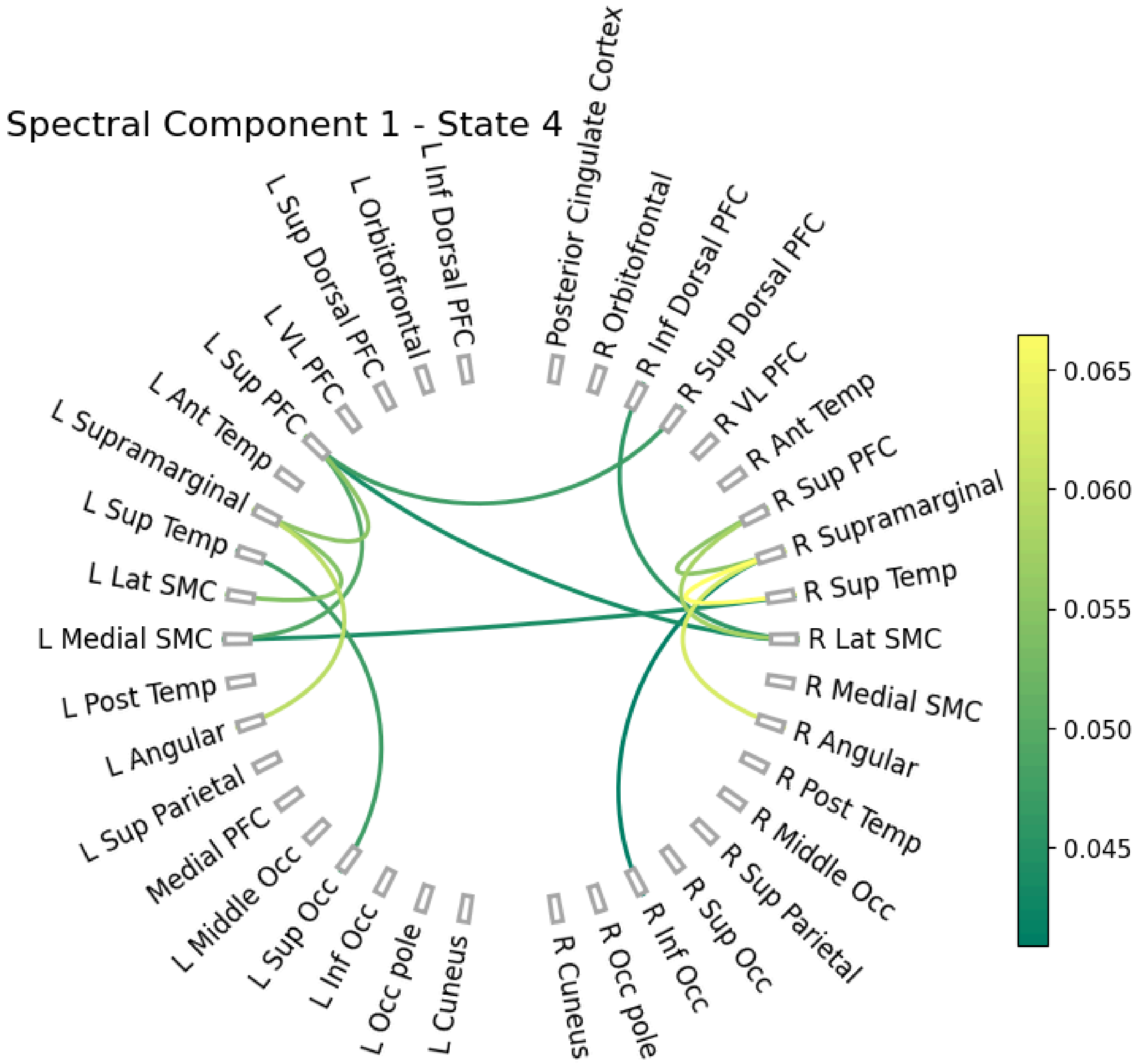
In [214…

```
connectivity_6states_SC1_S3 = connectivity_6states_SC1[2]

sc=0
title = 'Spectral Component 1 - State 3
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



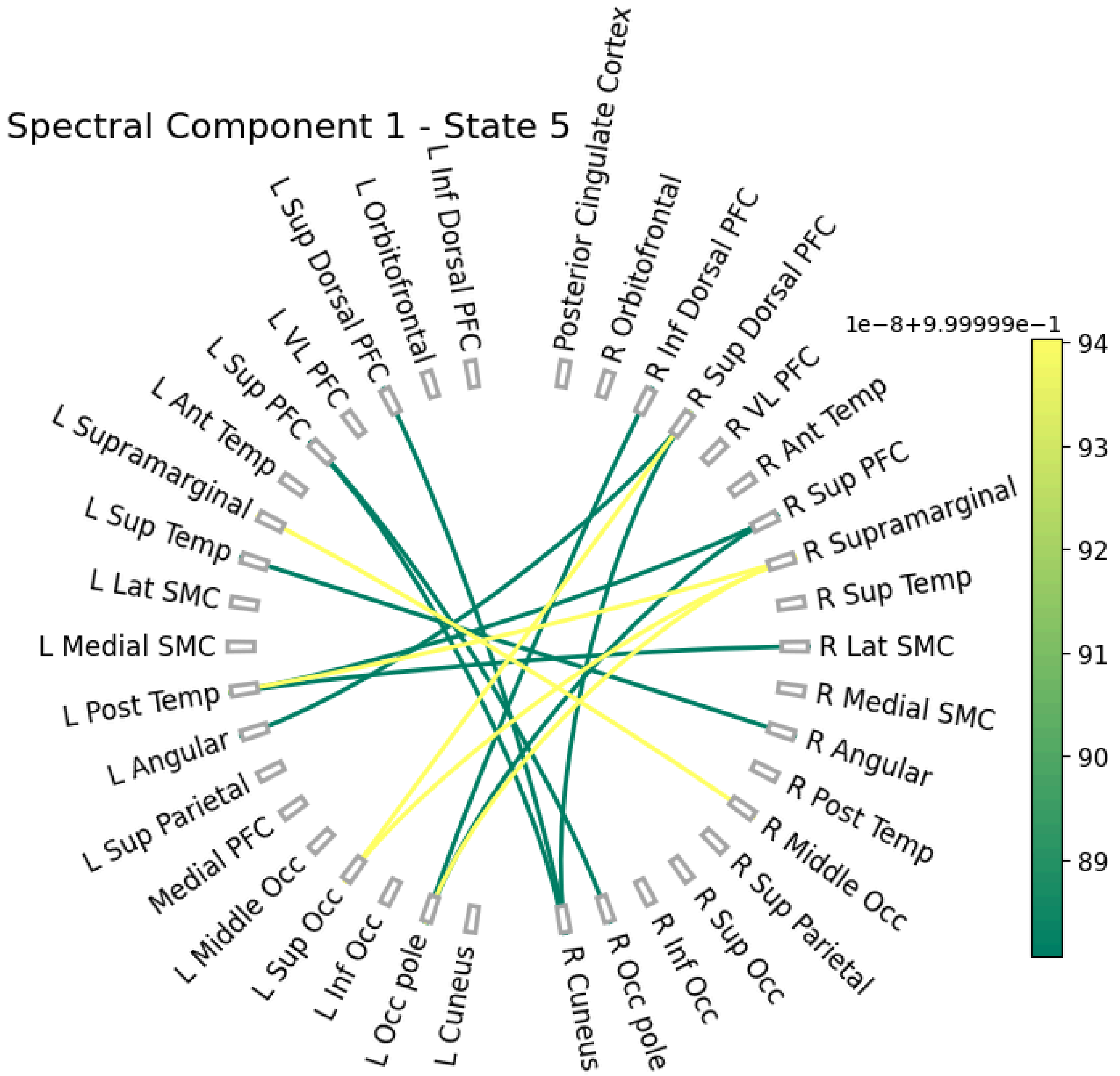
In [215…

```
connectivity_6states_SC1_S4 = connectivity_6states_SC1[3]

sc=0
title = 'Spectral Component 1 - State 4'
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



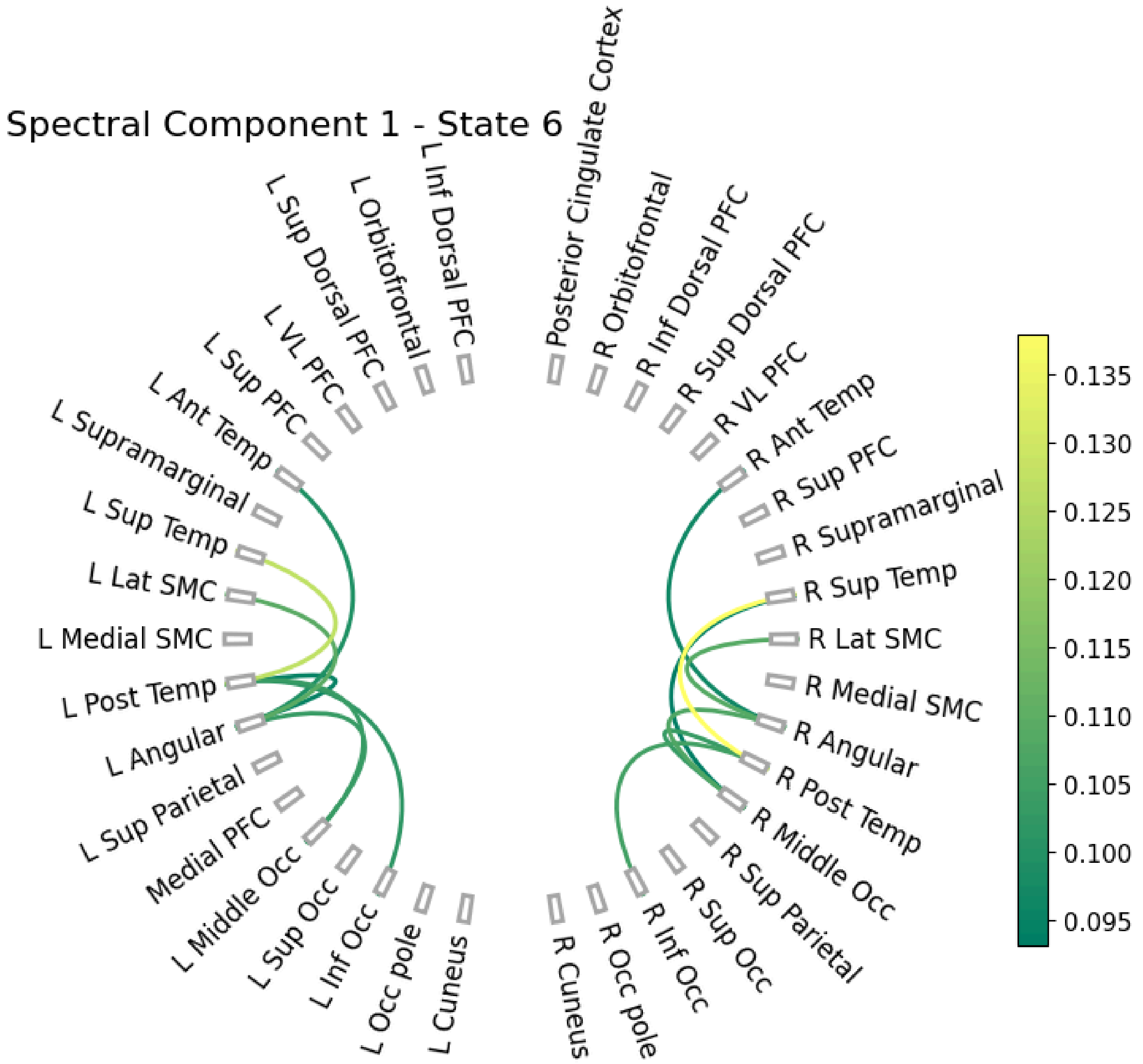
In [216…

```
connectivity_6states_SC1_S5 = connectivity_6states_SC1[4]

sc=0
title = 'Spectral Component 1 - State 5
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



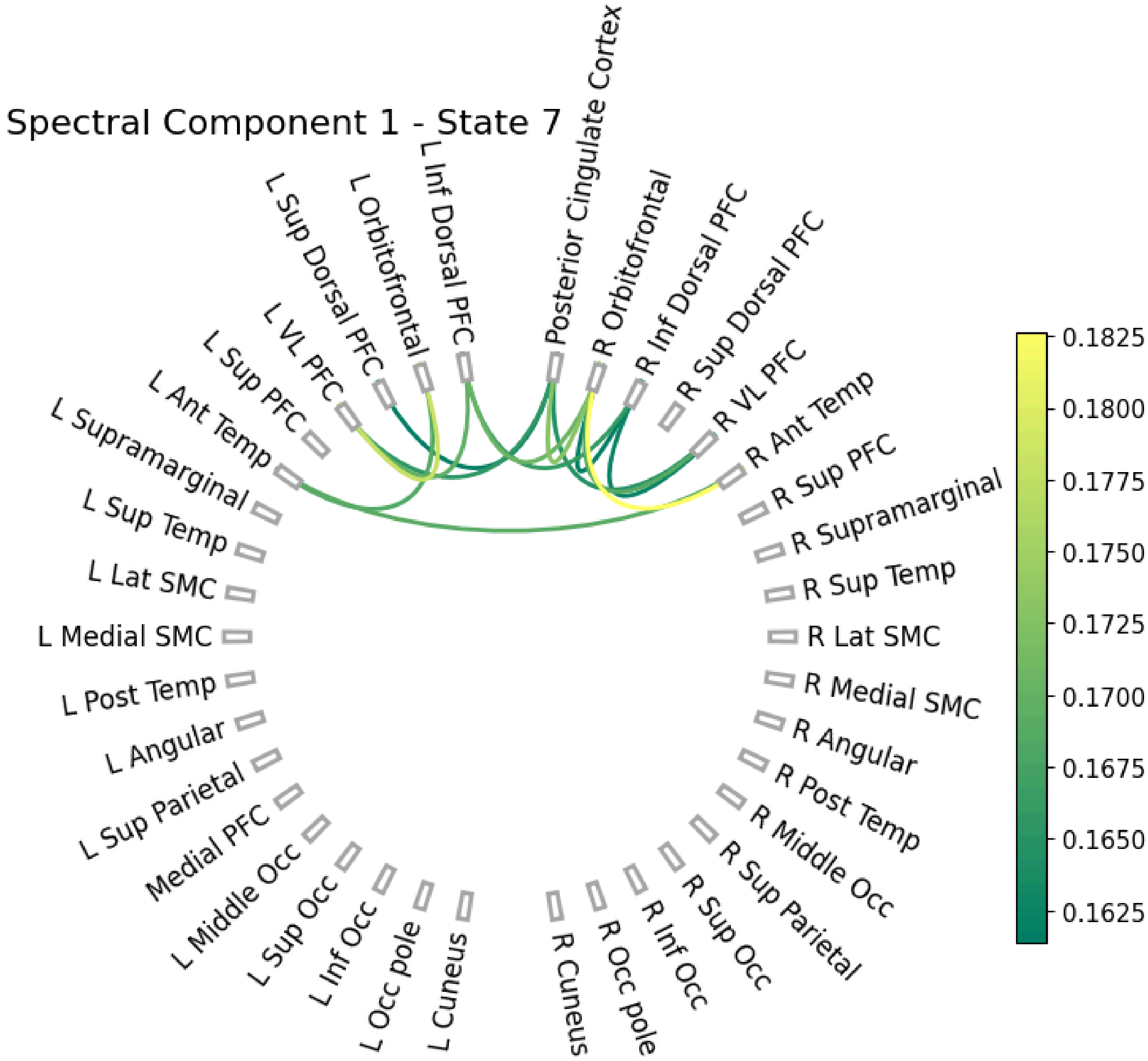
In [217…

```
connectivity_6states_SC1_S6 = connectivity_6states_SC1[5]

sc=0
title = 'Spectral Component 1 - State 6
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                               title=title, image_name=img_name, network=True
```



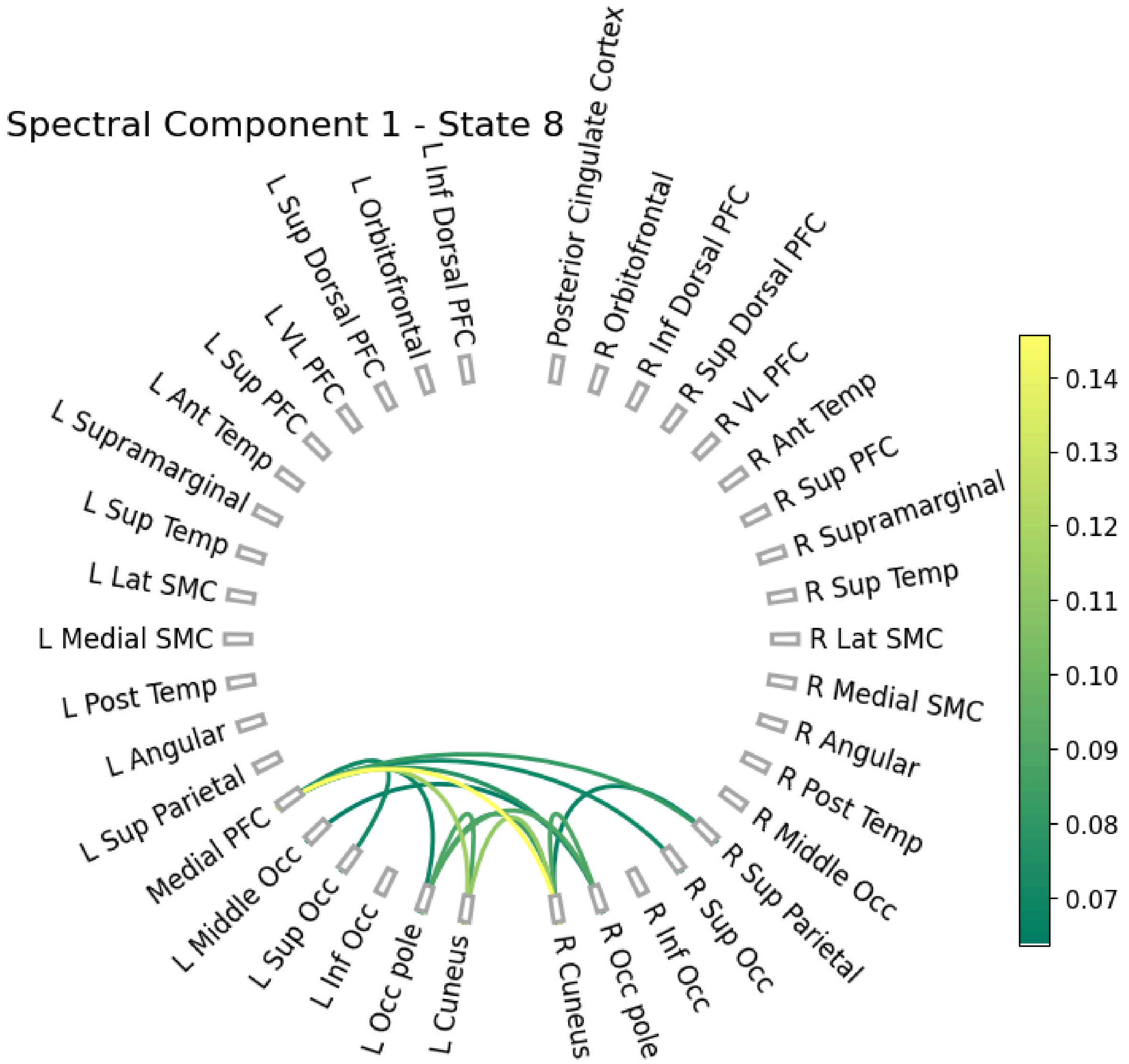
In [218…

```
connectivity_6states_SC1_S7 = connectivity_6states_SC1[6]

sc=0
title = 'Spectral Component 1 - State 7
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



In [219…

```
connectivity_6states_SC1_S8 = connectivity_6states_SC1[7]

sc=0
title = 'Spectral Component 1 - State 8
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



Data-driven thresholding: Gaussian Mixture Model (GMM)

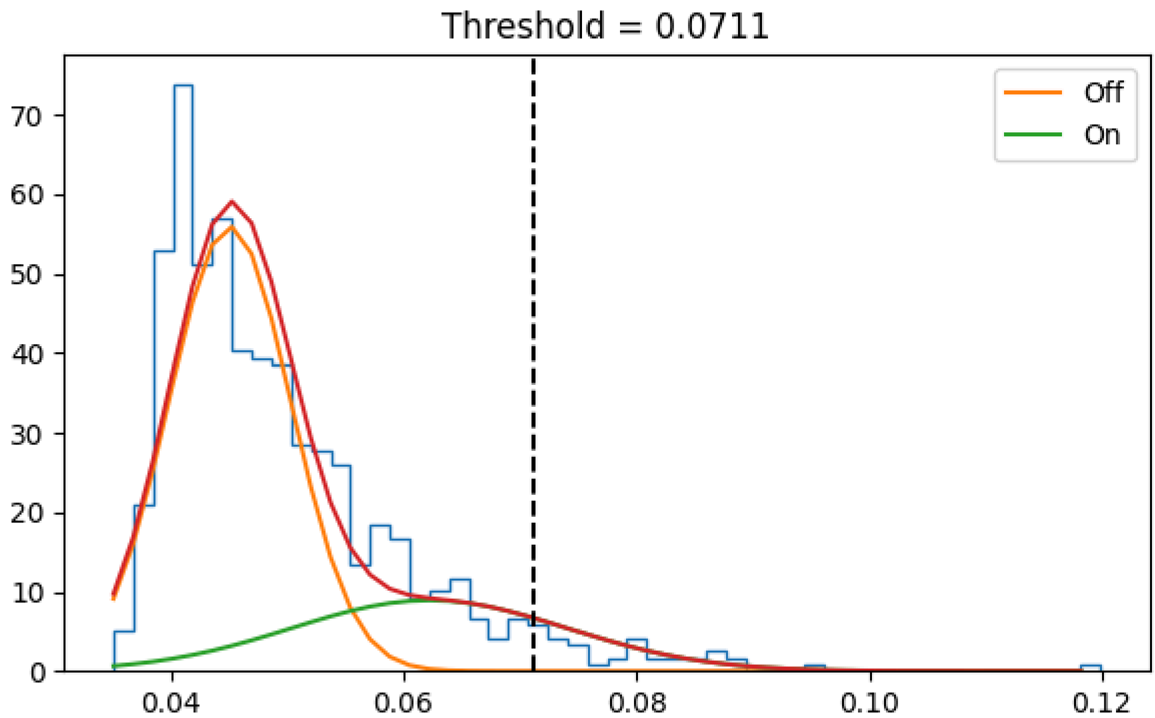
Spectral component 1

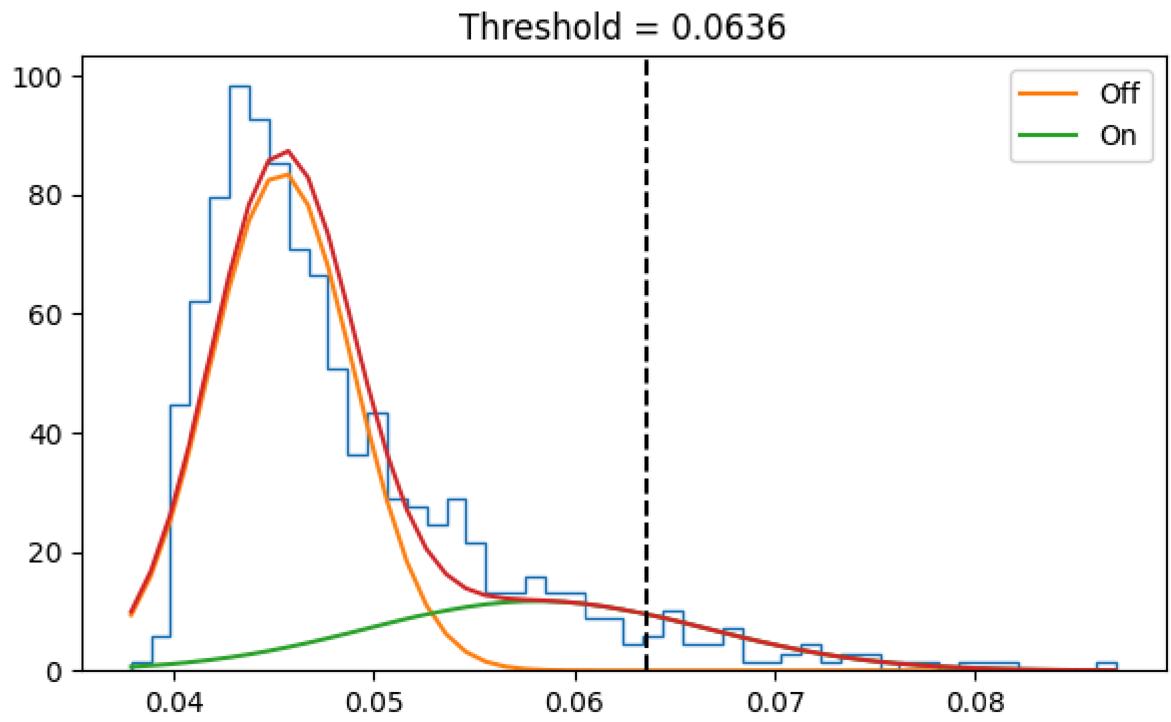
In [ ]:
```
mean_c = mean_c[:][:,np.array([True, True, True, True, False, True, True, Tı
print(np.shape(mean_c))
```

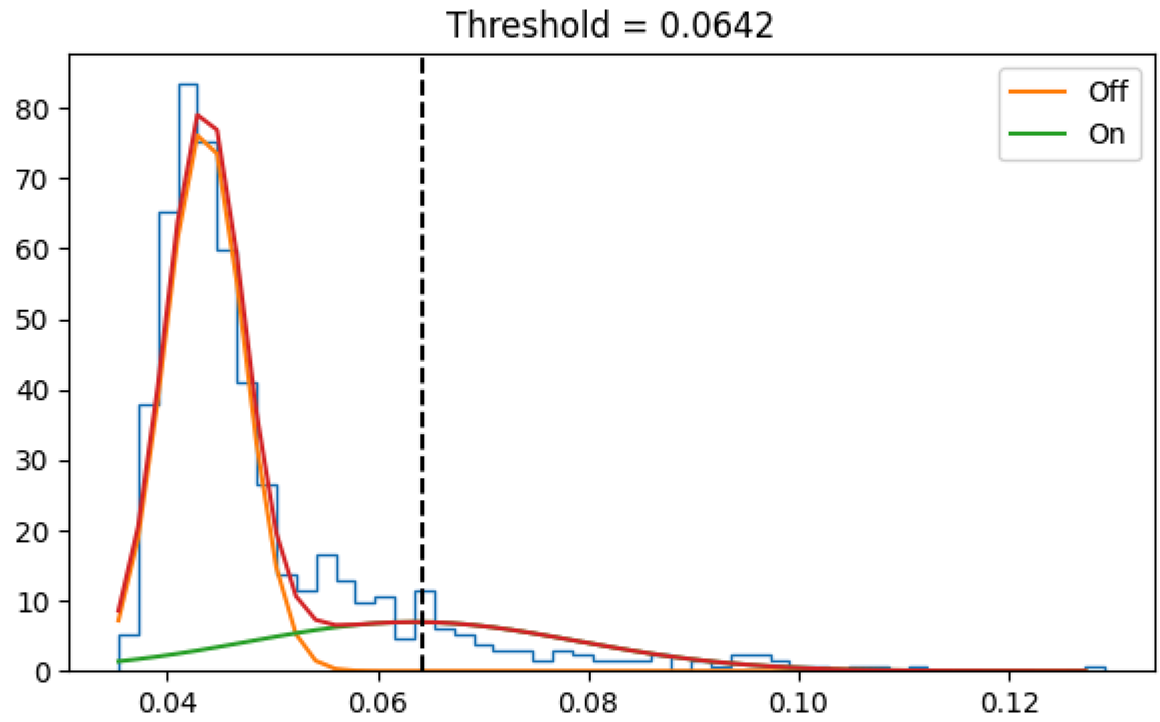
In [158…
```
## This only needs to be ran once (it does the GMM data-driven thresholding

sc = 0

# Threshold each network using a GMM
thres_mean_c = connectivity.gmm_threshold(
    mean_c,
    p_value=0.05,
    keep_positive_only=True,
    #subtract_mean=True,
    show=True,
)
print(thres_mean_c.shape)
```

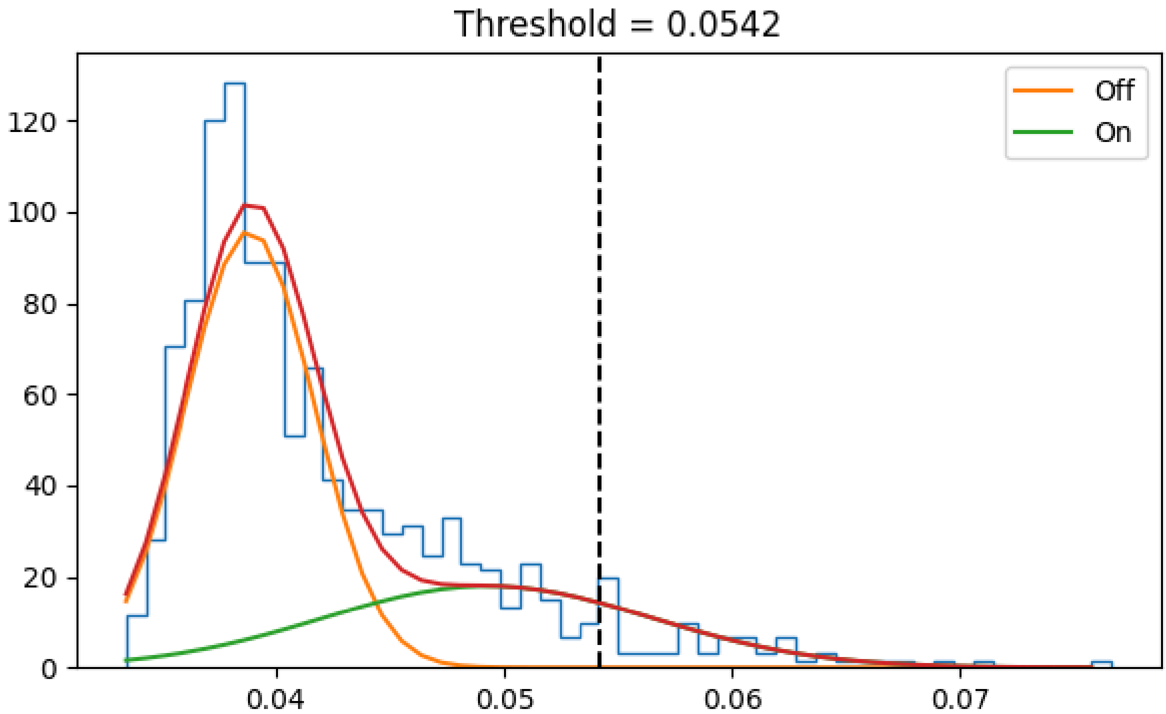
```
os.makedirs(model_name + "/data/Images" + "/Basic_Coherence_GMM", exist_ok=T

# Plot
connectivity.save(
    thres_mean_c,
    parcellation_file="/home/olivierb/38_parcels.nii",
    component=sc,
    filename=model_name + "/data/Images/Basic_Coherence_GMM/coh_Spectral_Com
)
```

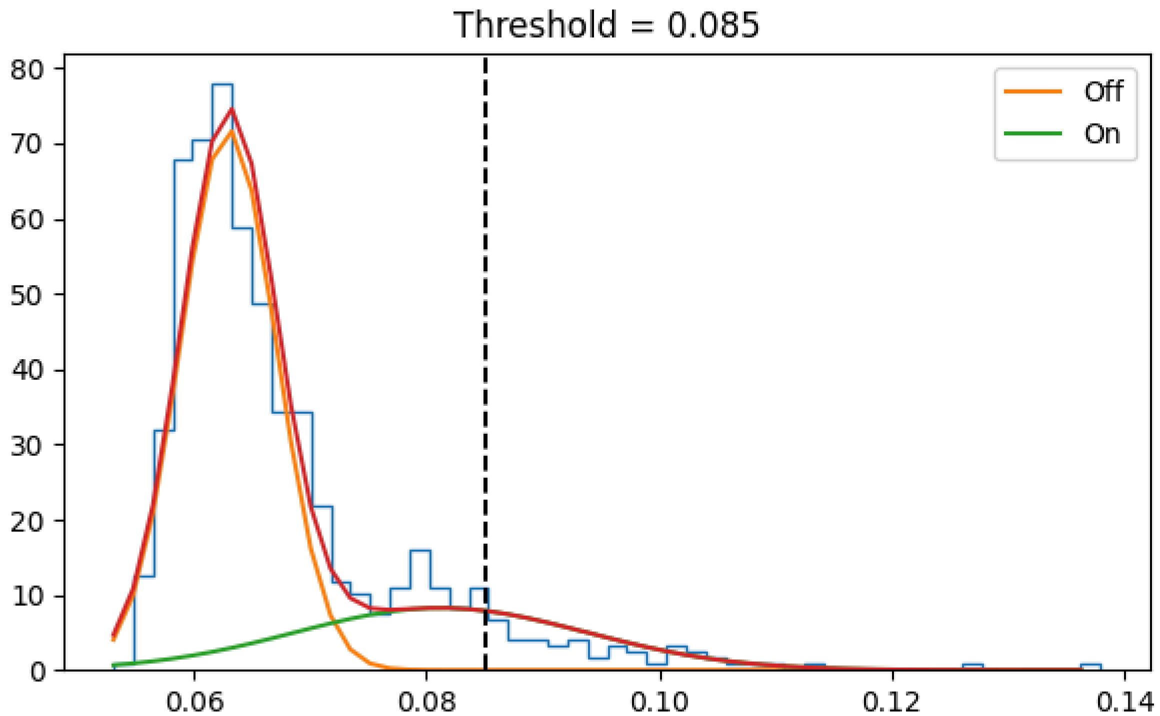
```
/home/olivierb/osl-dynamics/osl_dynamics/utils/plotting.py:72: RuntimeWarni
ng: More than 20 figures have been opened. Figures created through the pypl
ot interface (`matplotlib.pyplot.figure`) are retained until explicitly clo
sed and may consume too much memory. (To control this warning, see the rcPa
ram `figure.max_open_warning`). Consider using `matplotlib.pyplot.close()`.
  fig, ax = plt.subplots(*args, **kwargs)
(4, 7, 38, 38)
Saving images: 100%|██████████| 7/7 [00:09<00:00,  1.35s/it]
```

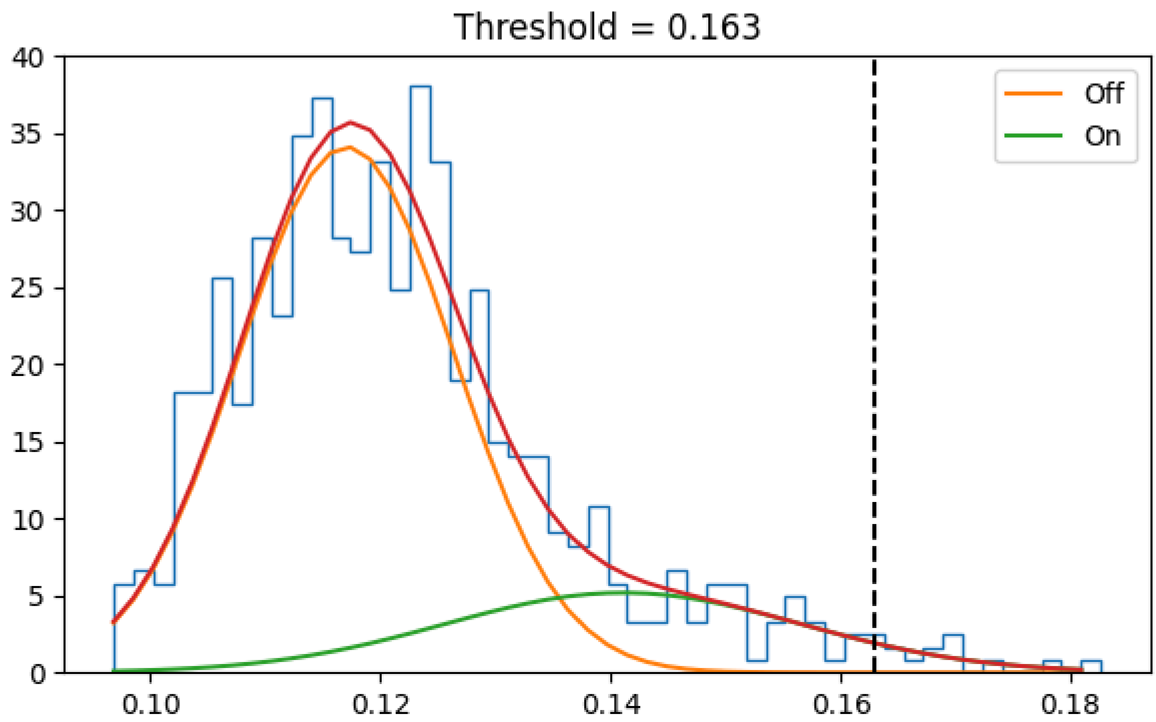


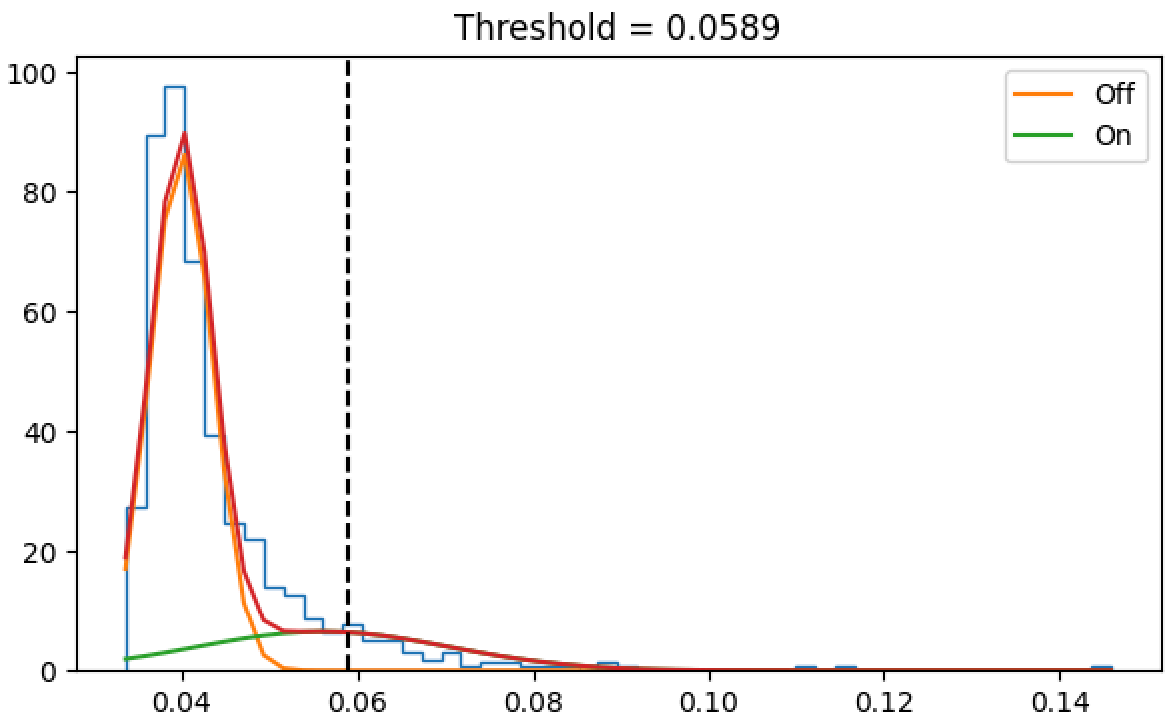

Threshold = 0.0636
Off
On
0
20
40
60
80
100
0.04
0.05
0.06
0.07
0.08

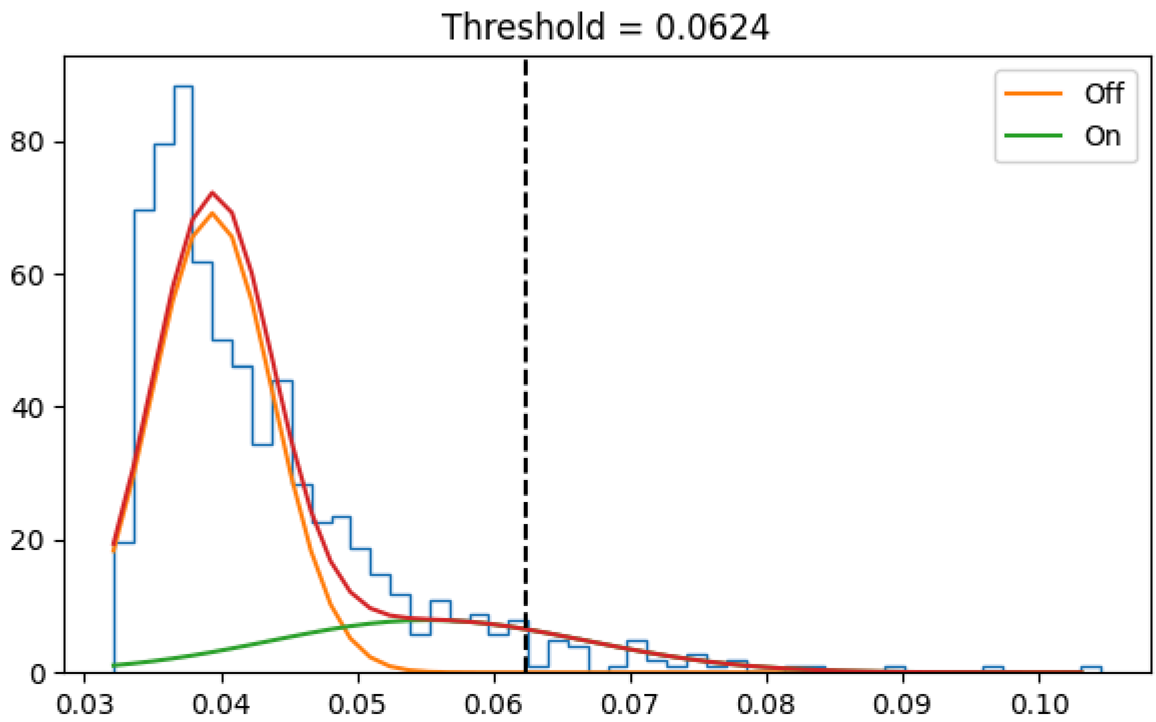

Threshold = 0.0642
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.06
0.08
0.10
0.12

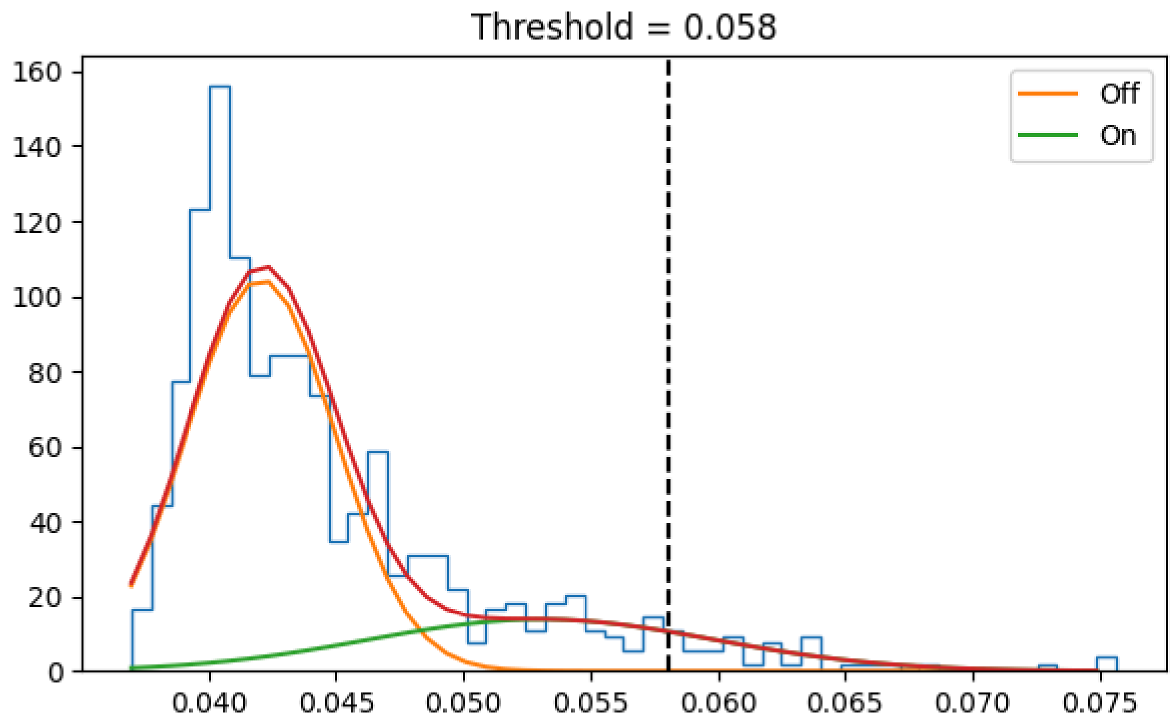

Threshold = 0.0542
Off
On
0
20
40
60
80
100
120
0.04
0.05
0.06
0.07

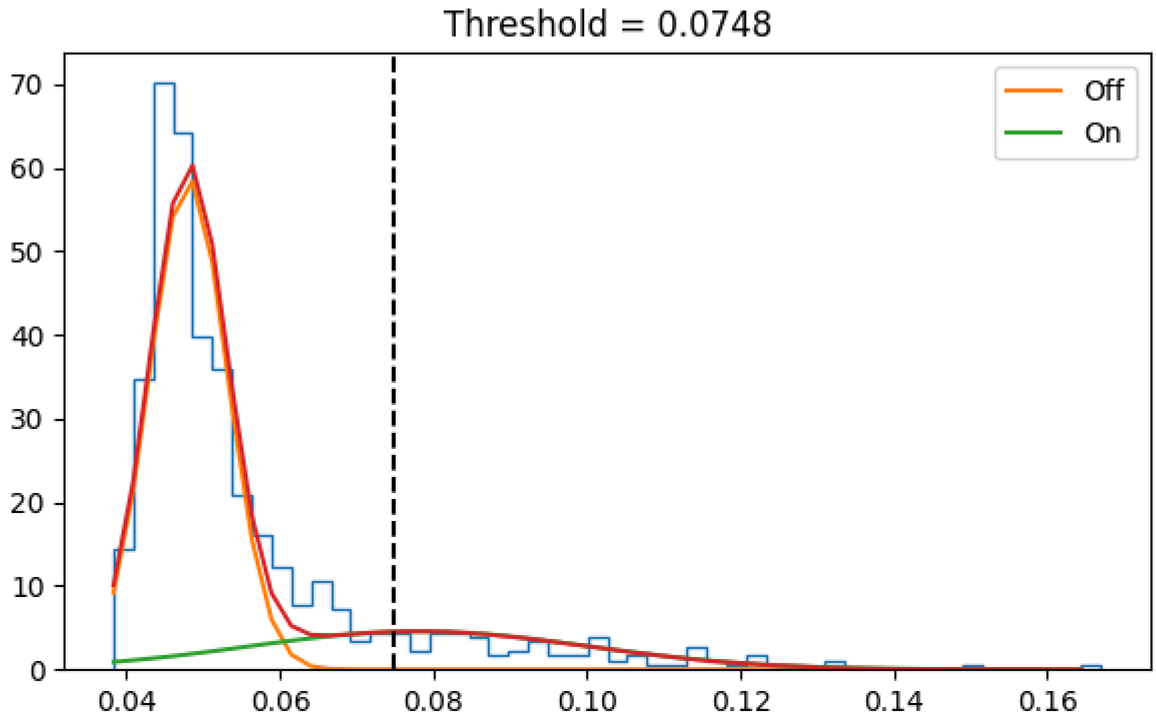

Threshold = 0.085
Off
On
0
10
20
30
40
50
60
70
80
0.06
0.08
0.10
0.12
0.14

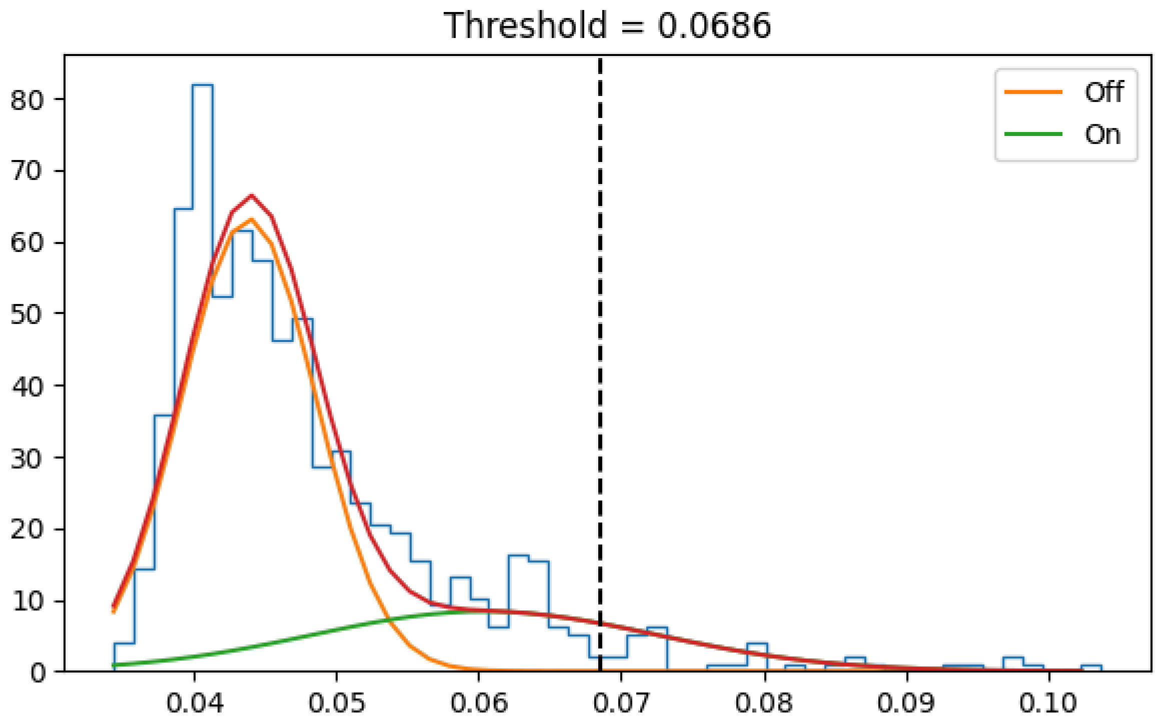

Threshold = 0.163
Off
On
0
5
10
15
20
25
30
35
40
0.10
0.12
0.14
0.16
0.18

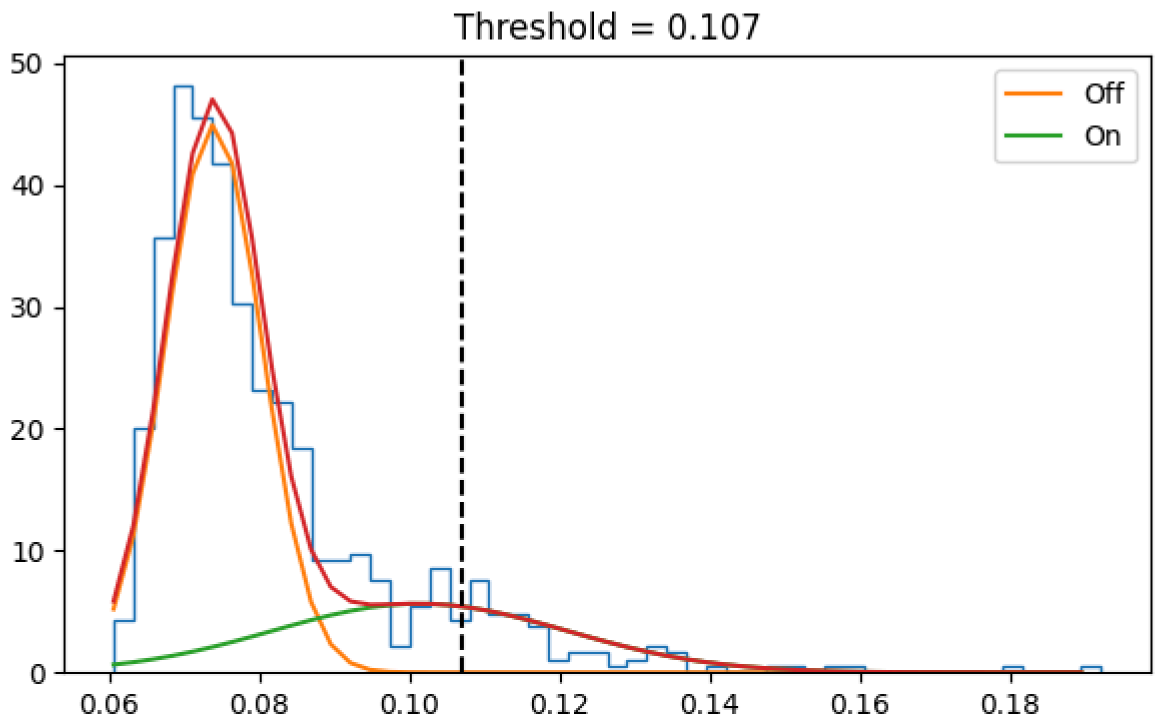

Threshold = 0.0589
Off
On
0
20
40
60
80
100
0.04
0.06
0.08
0.10
0.12
0.14

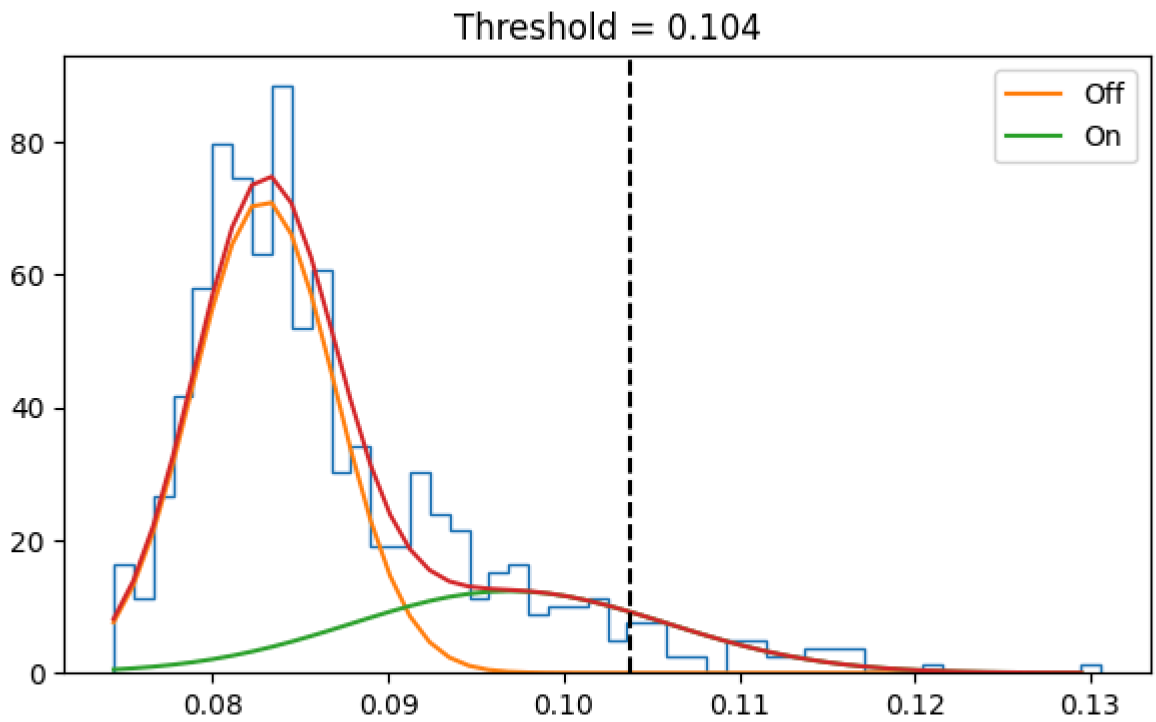

Threshold = 0.0624
Off
On
0
20
40
60
80
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10

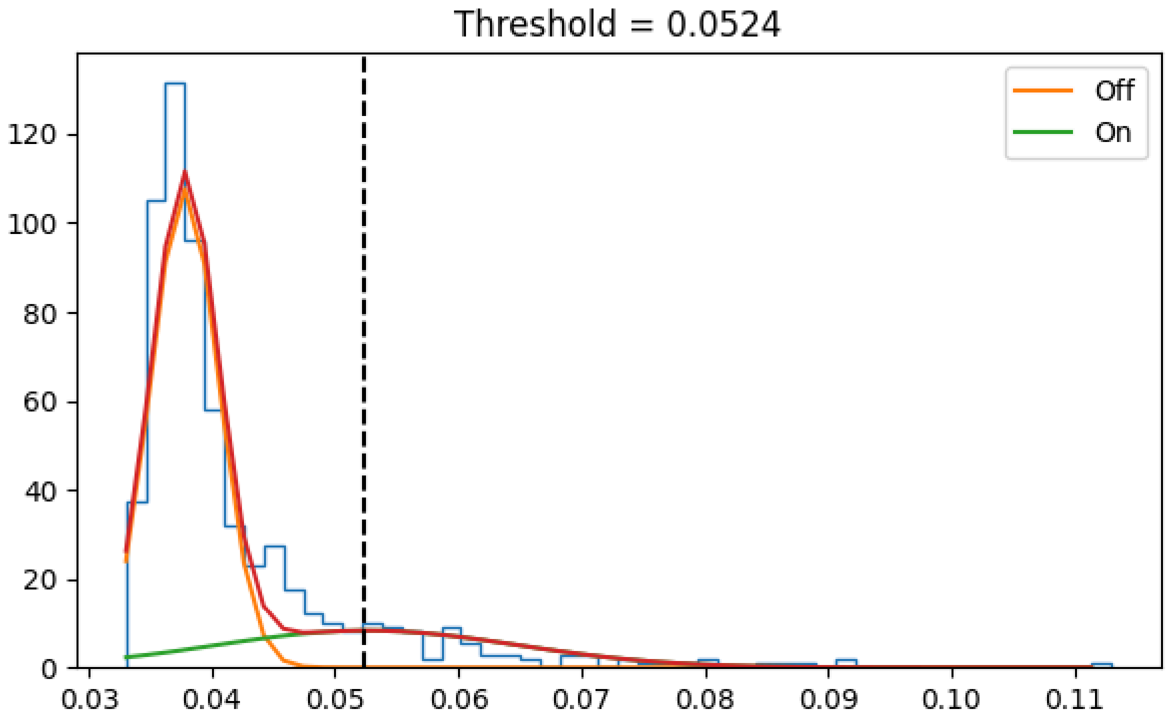

Threshold = 0.058
Off
On
0
20
40
60
80
100
120
140
160
0.040
0.045
0.050
0.055
0.060
0.065
0.070
0.075

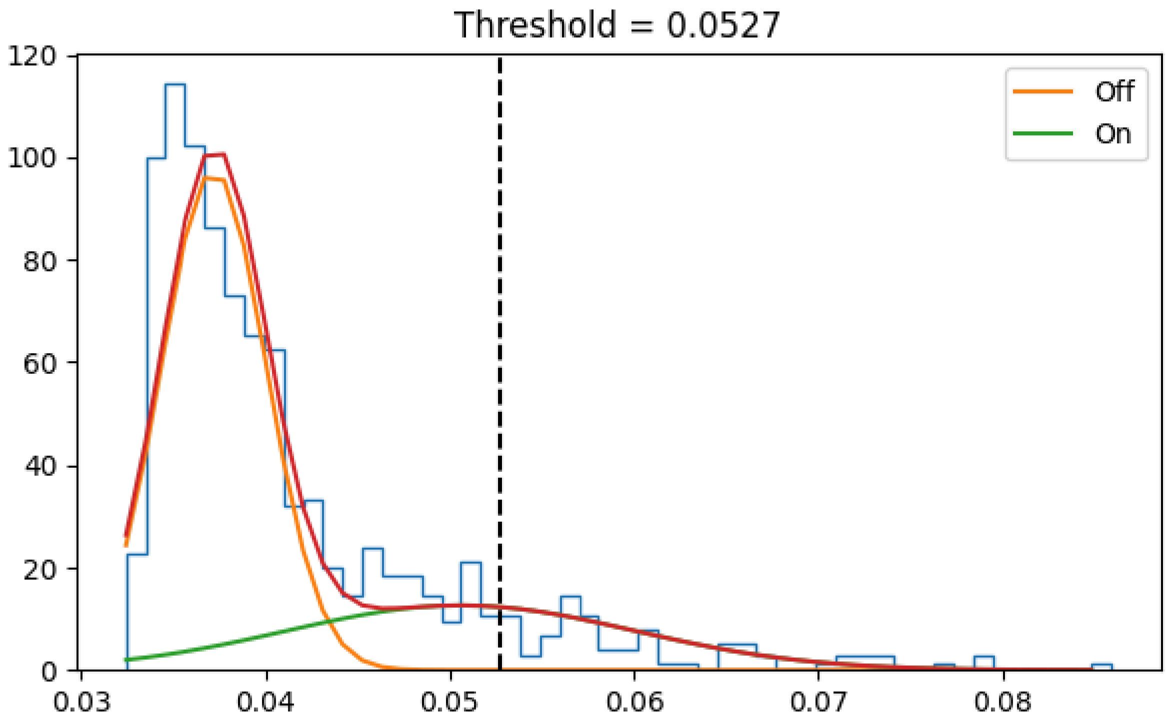

Threshold = 0.0748
Off
On
0
10
20
30
40
50
60
70
0.04
0.06
0.08
0.10
0.12
0.14
0.16

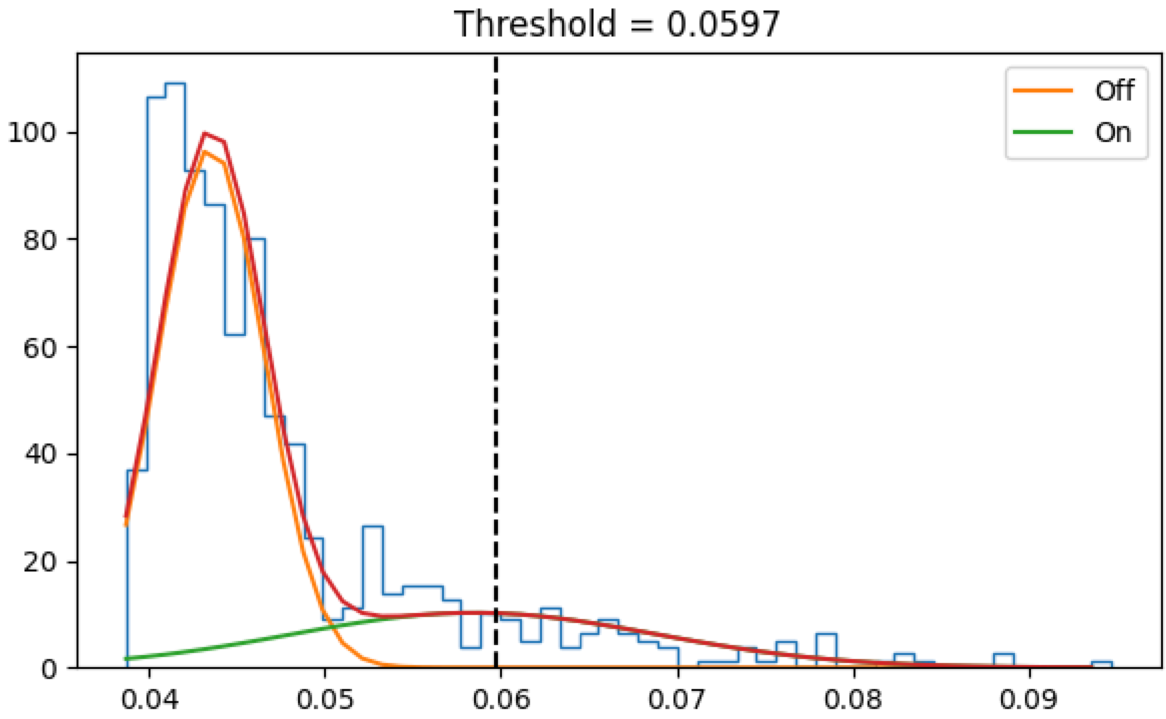

Threshold = 0.0686
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.05
0.06
0.07
0.08
0.09
0.10

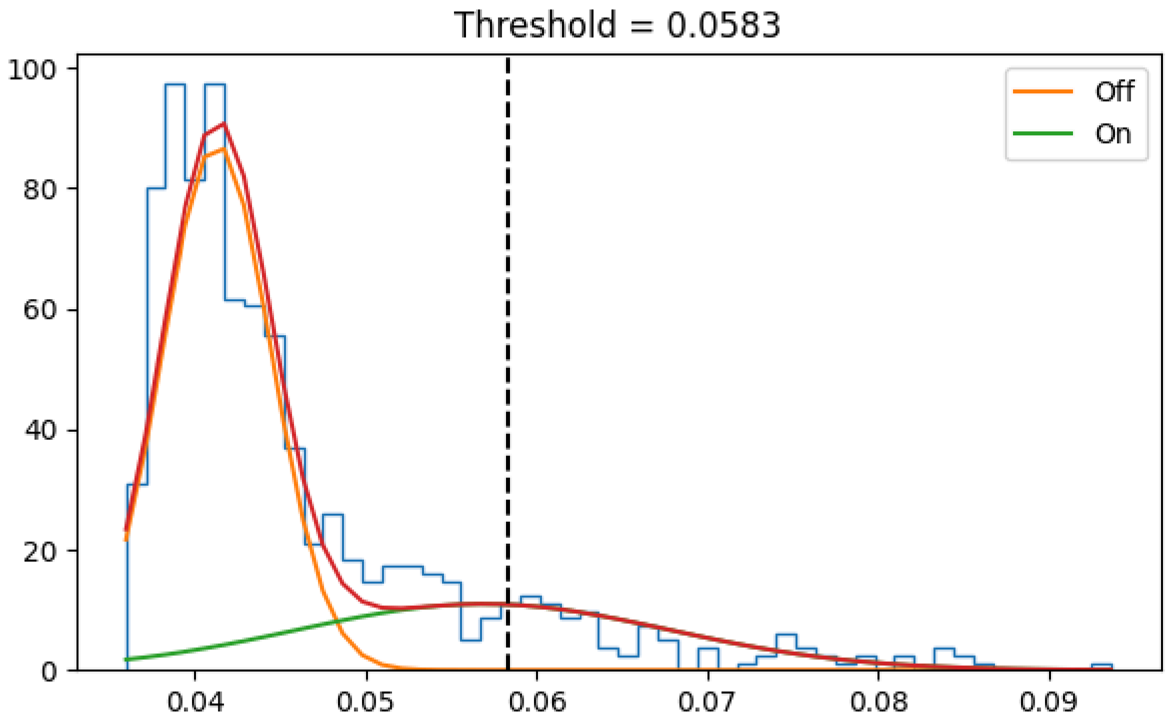

Threshold = 0.107
Off
On
0
10
20
30
40
50
0.06
0.08
0.10
0.12
0.14
0.16
0.18

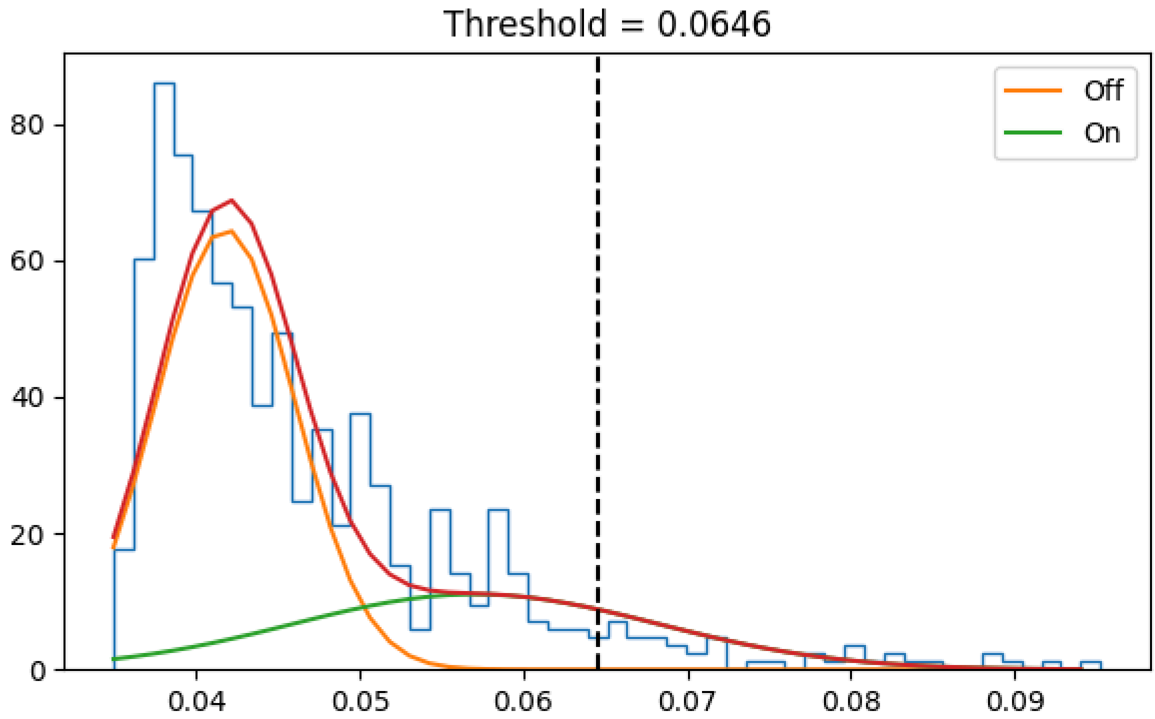

Threshold = 0.104
Off
On
0
20
40
60
80
0.08
0.09
0.10
0.11
0.12
0.13

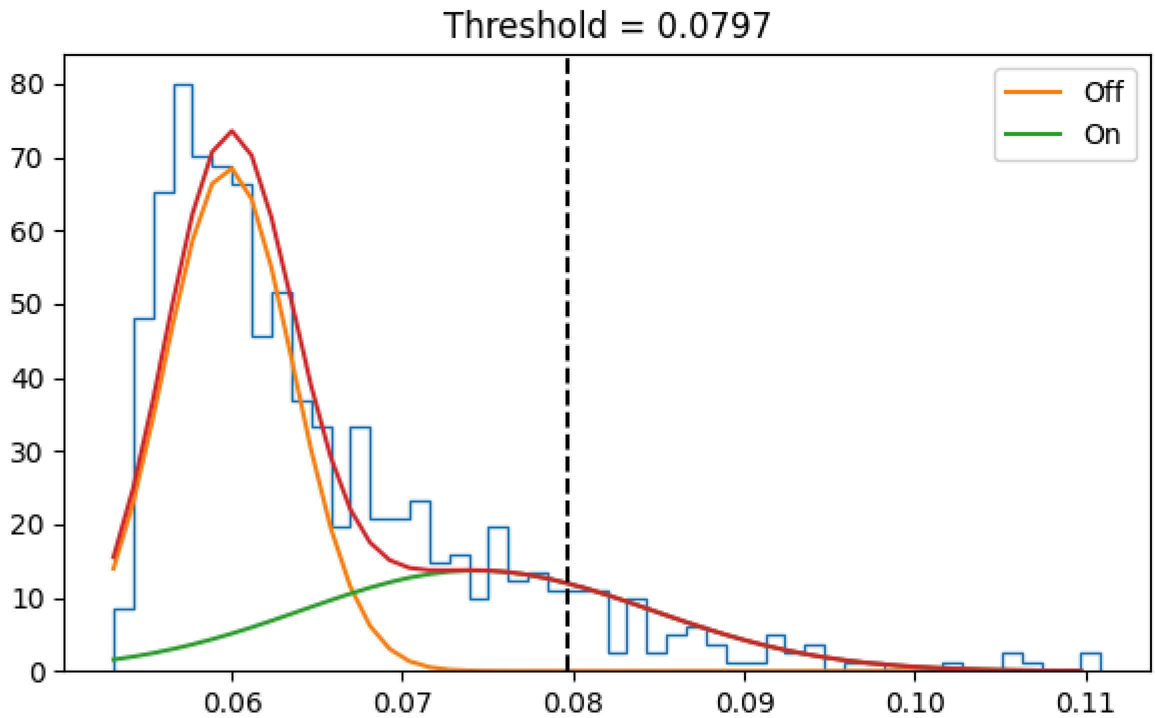

Threshold = 0.0524
Off
On
0
20
40
60
80
100
120
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10
0.11

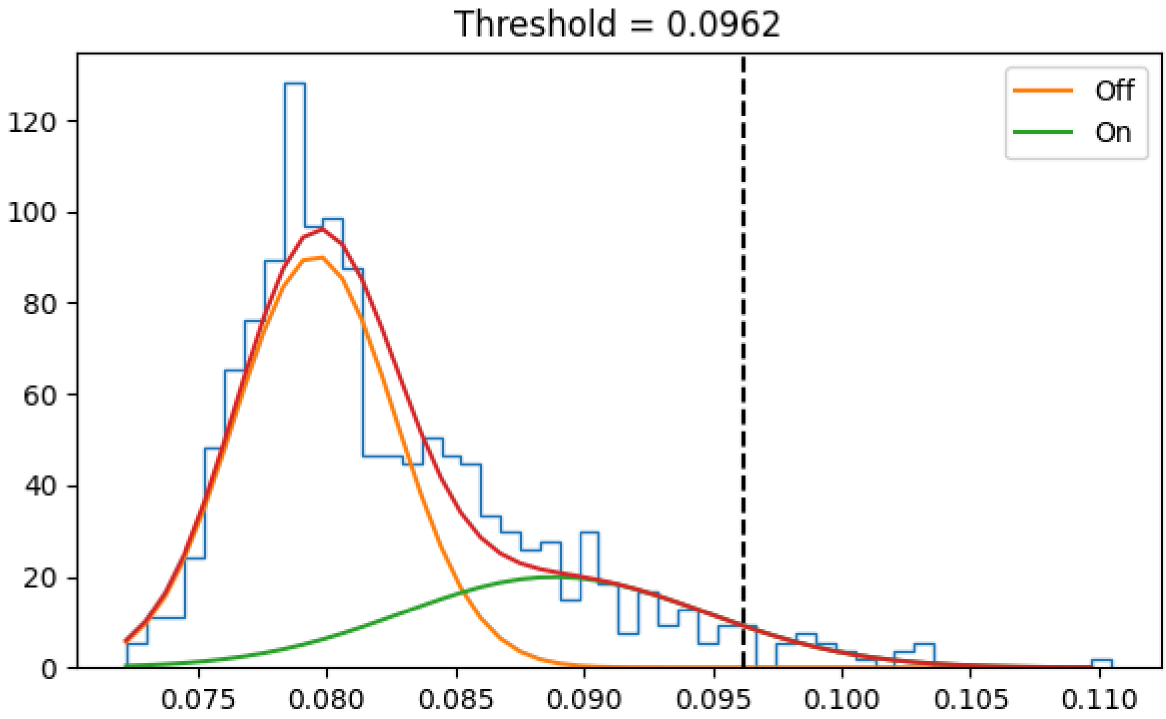

Threshold = 0.0527
Off
On
0
20
40
60
80
100
120
0.03
0.04
0.05
0.06
0.07
0.08

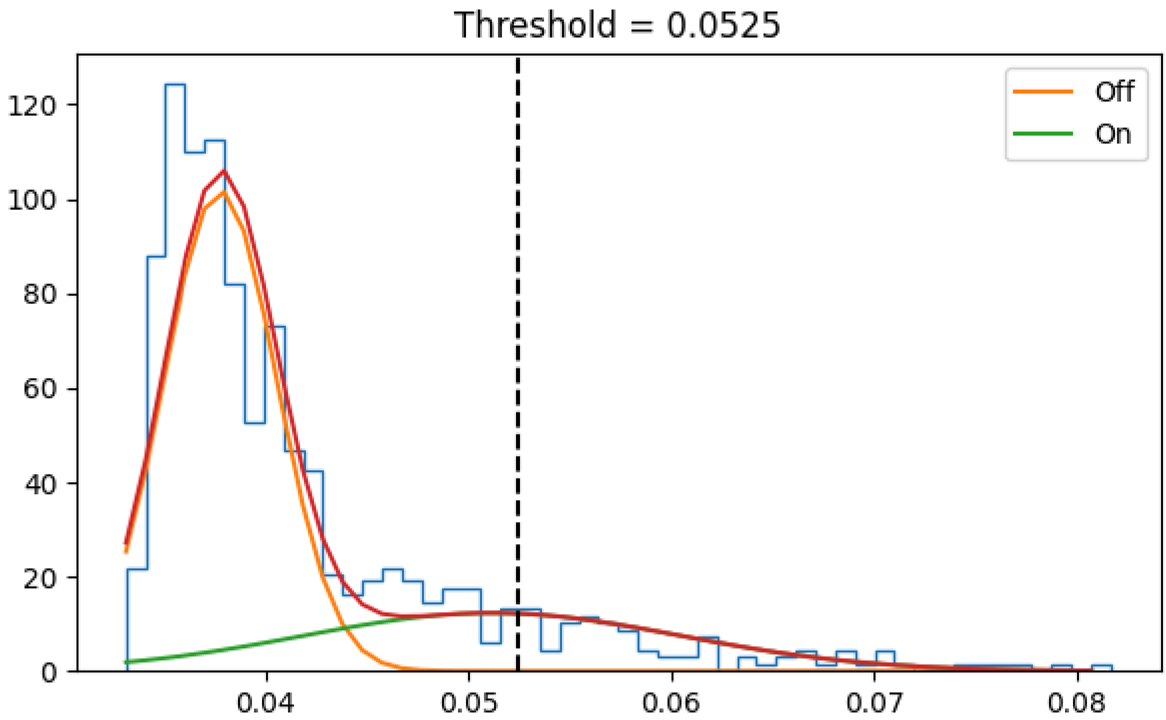

Threshold = 0.0597
Off
On
0
20
40
60
80
100
0.04
0.05
0.06
0.07
0.08
0.09

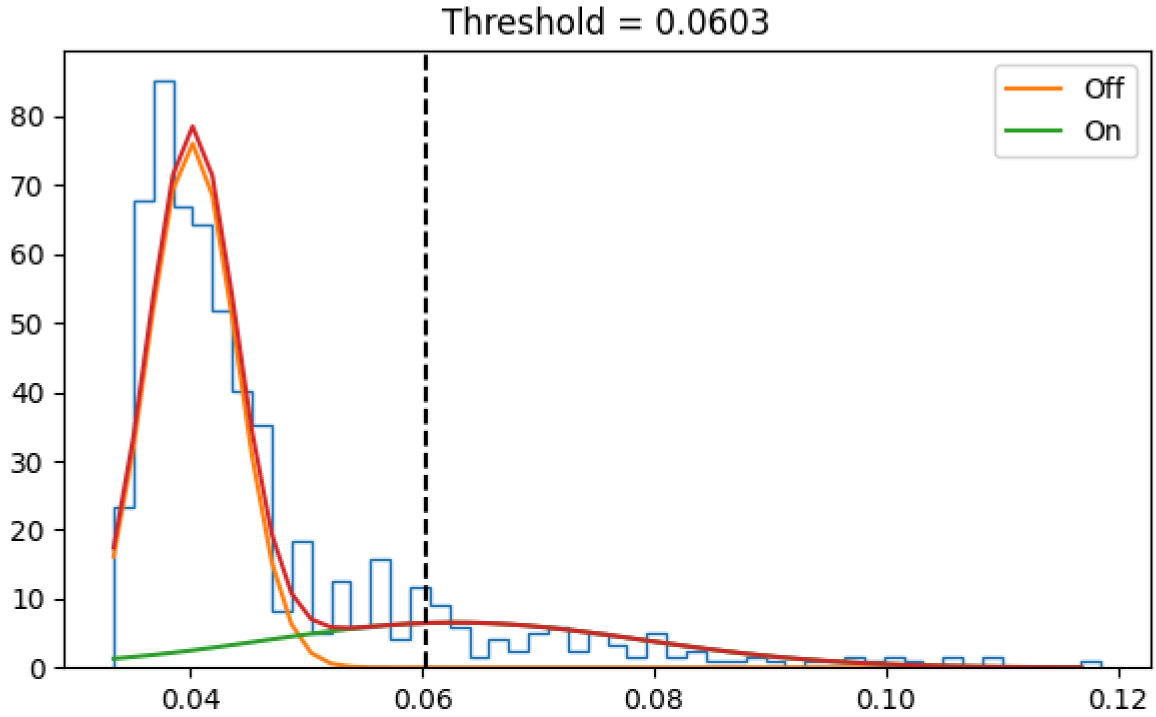

Threshold = 0.0583
Off
On
0
20
40
60
80
100
0.04
0.05
0.06
0.07
0.08
0.09

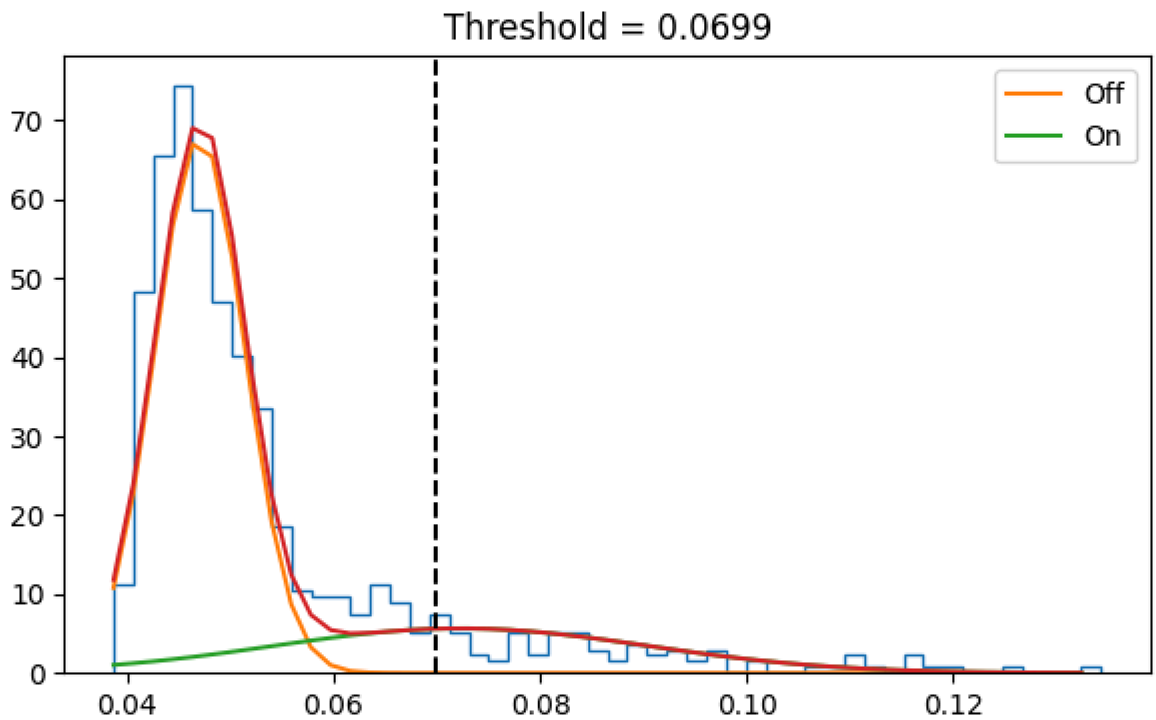

Threshold = 0.0646
Off
On
80
60
40
20
0
0.04
0.05
0.06
0.07
0.08
0.09

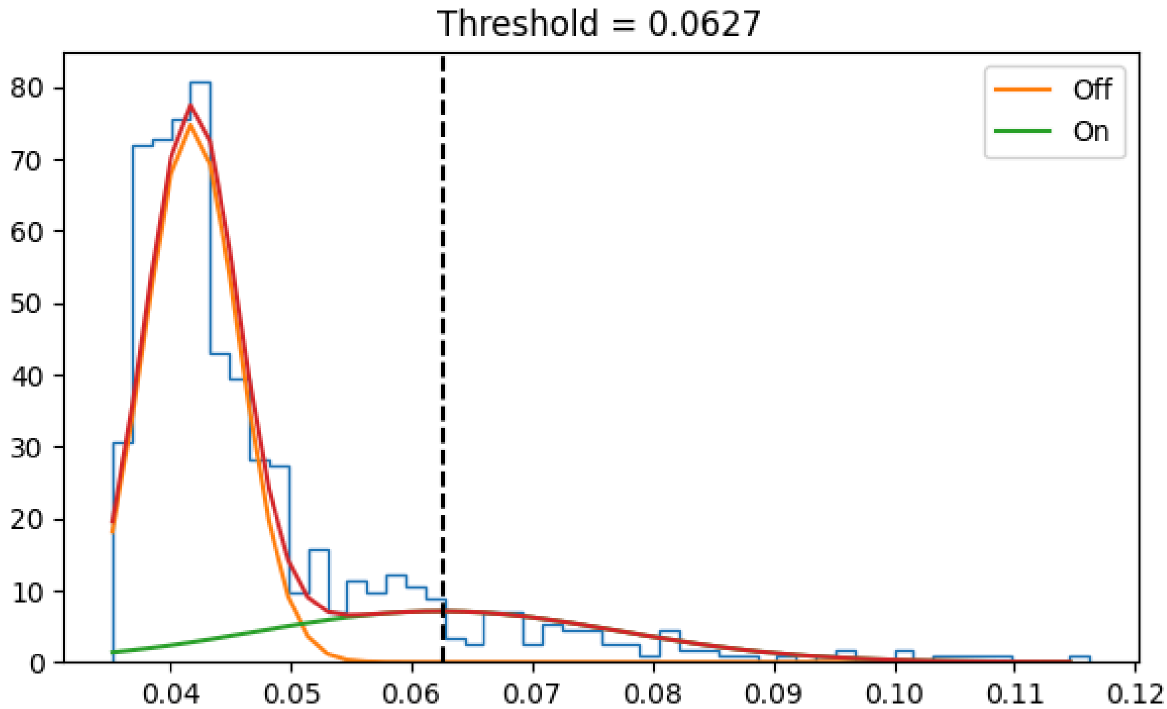

Threshold = 0.0797
Off
On
80
70
60
50
40
30
20
10
0
0.06
0.07
0.08
0.09
0.10
0.11

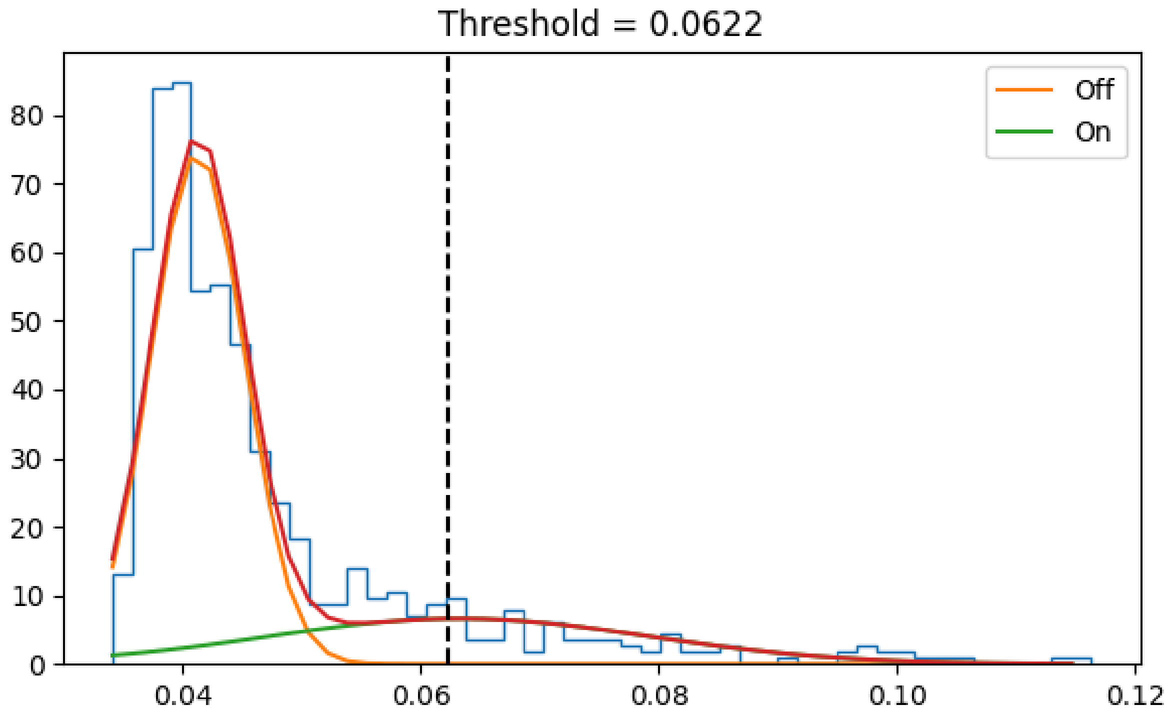

Threshold = 0.0962
Off
On
0
20
40
60
80
100
120
0.075
0.080
0.085
0.090
0.095
0.100
0.105
0.110

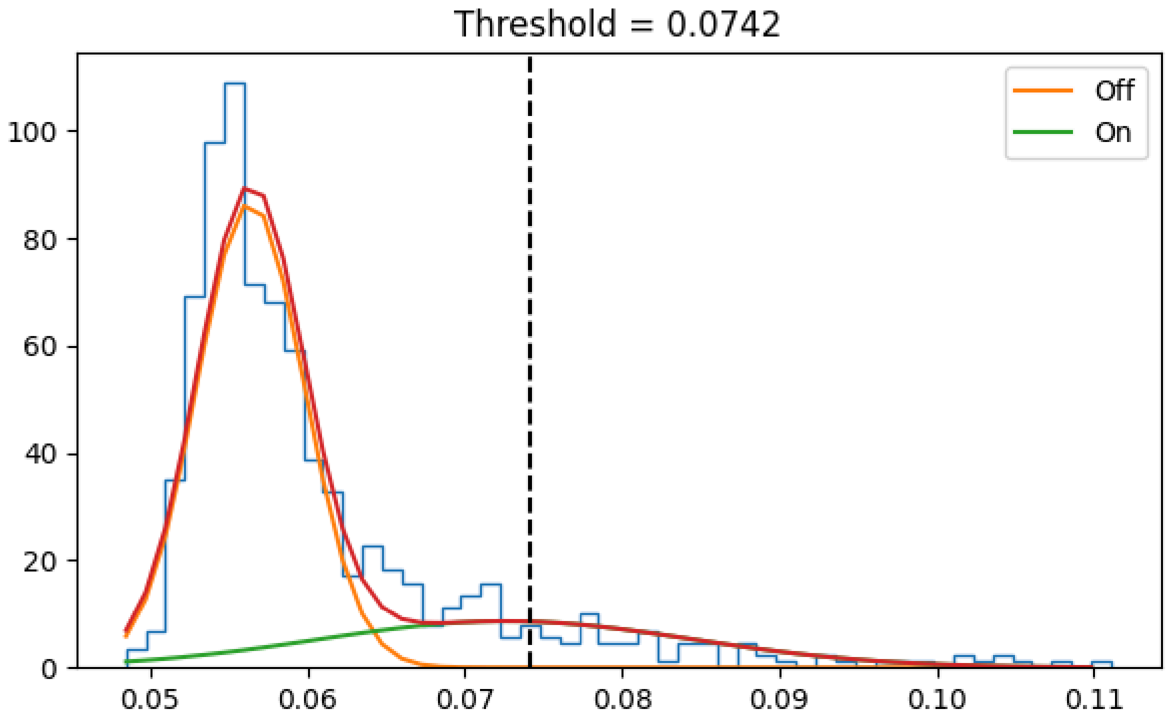

Threshold = 0.0525
Off
On
0
20
40
60
80
100
120
0.04
0.05
0.06
0.07
0.08

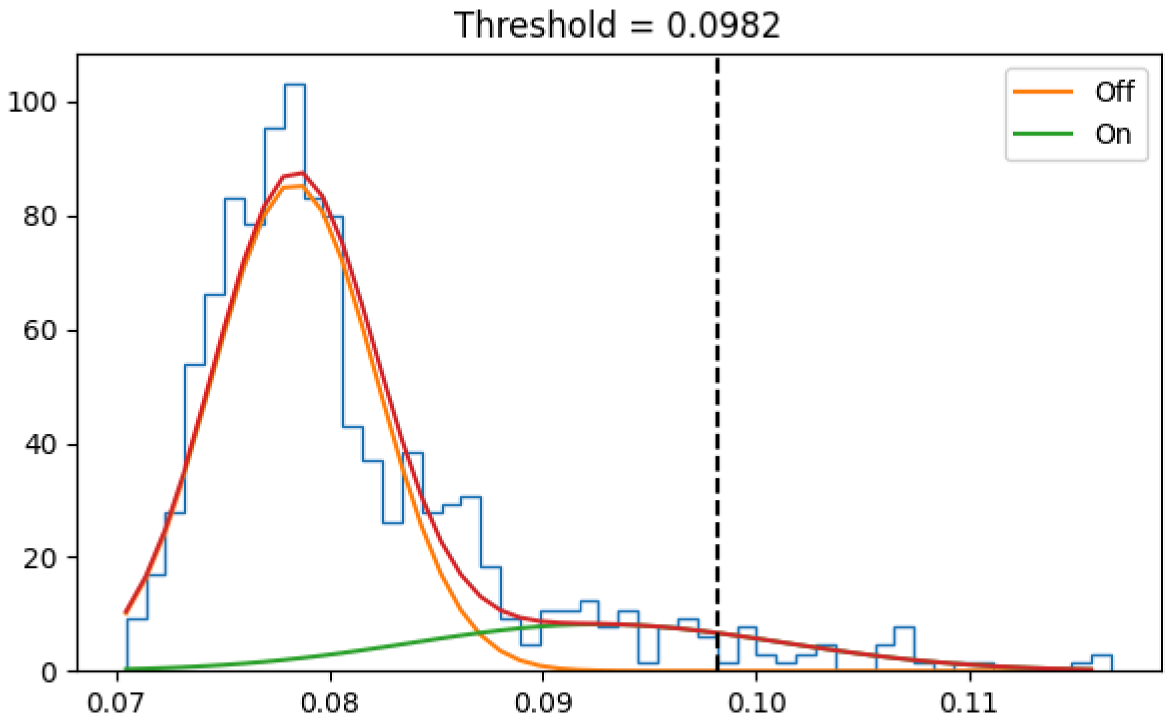

Threshold = 0.0603
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.06
0.08
0.10
0.12

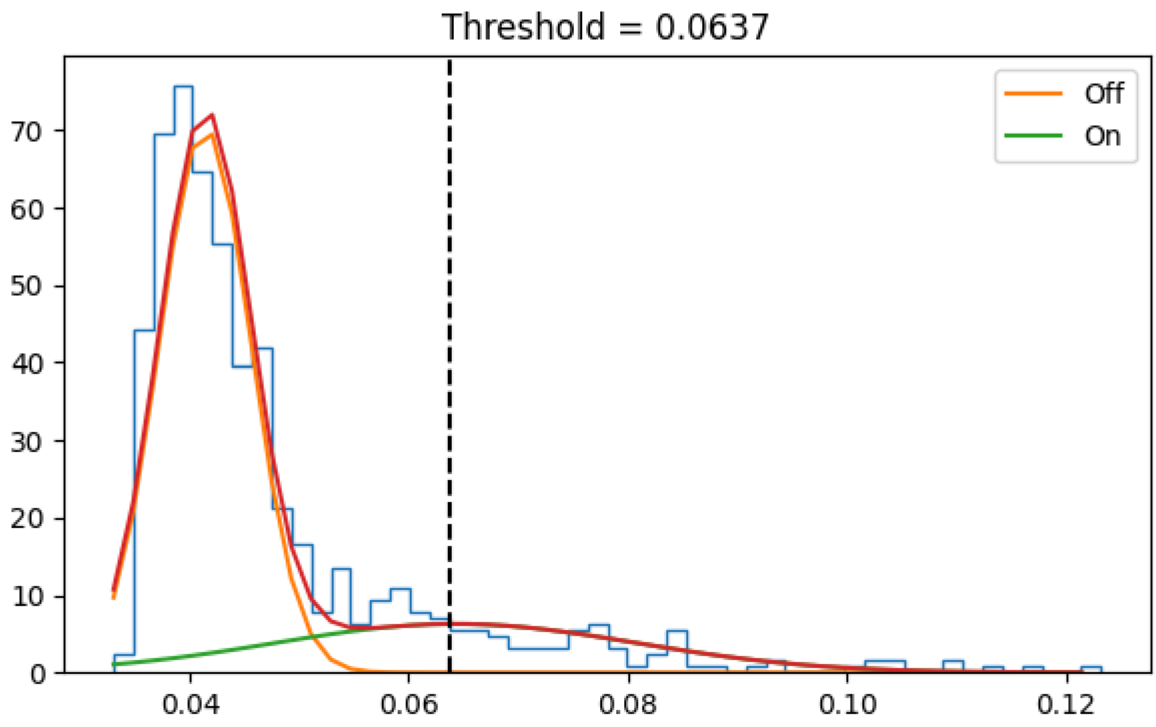

Threshold = 0.0699
Off
On
0
10
20
30
40
50
60
70
0.04
0.06
0.08
0.10
0.12


Threshold = 0.0627
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.05
0.06
0.07
0.08
0.09
0.10
0.11
0.12


Threshold = 0.0622
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.06
0.08
0.10
0.12

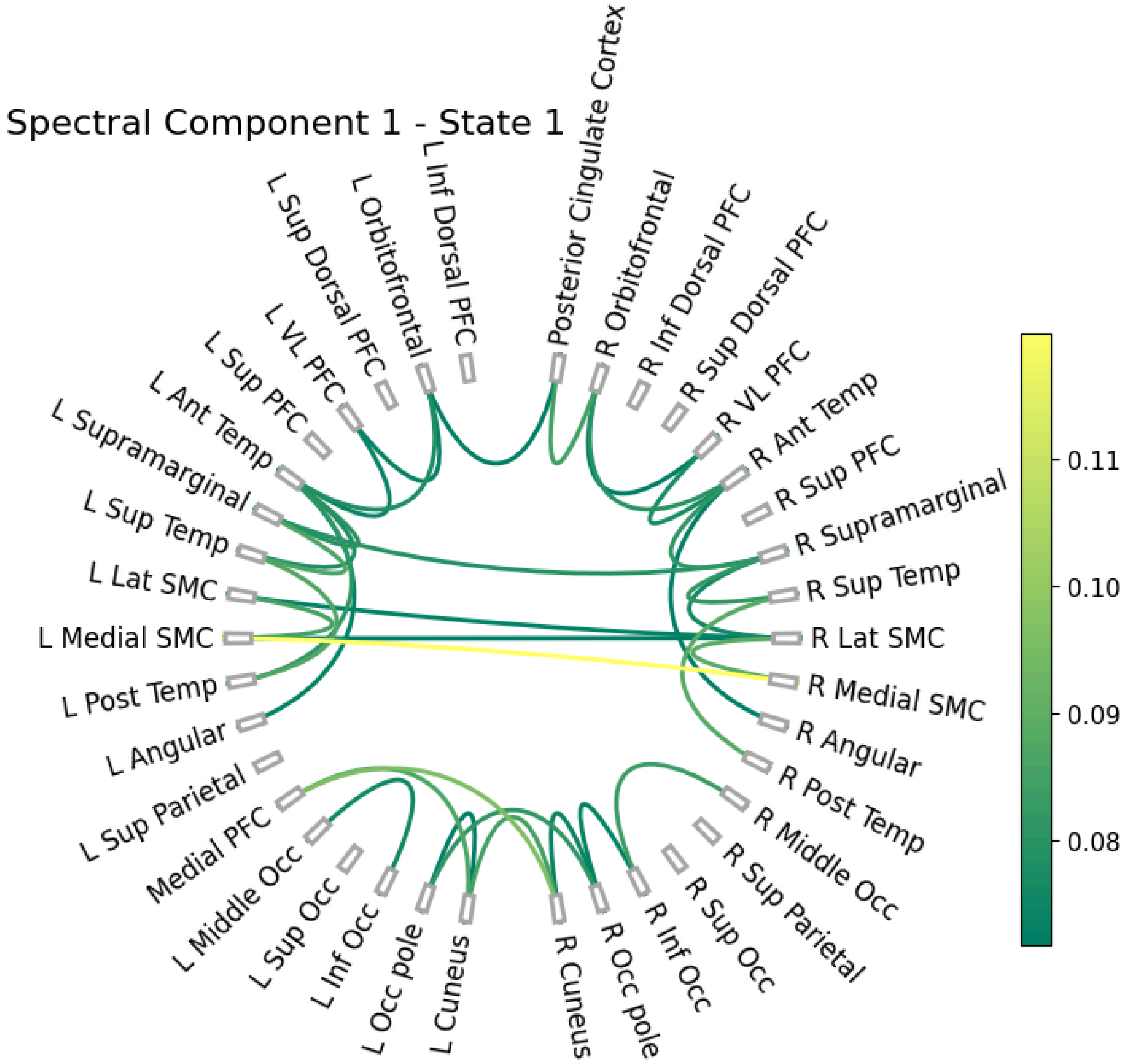

Threshold = 0.0742
Off
On
0
20
40
60
80
100
0.05
0.06
0.07
0.08
0.09
0.10
0.11


Threshold = 0.0982
Off
On
0
20
40
60
80
100
0.07
0.08
0.09
0.10
0.11



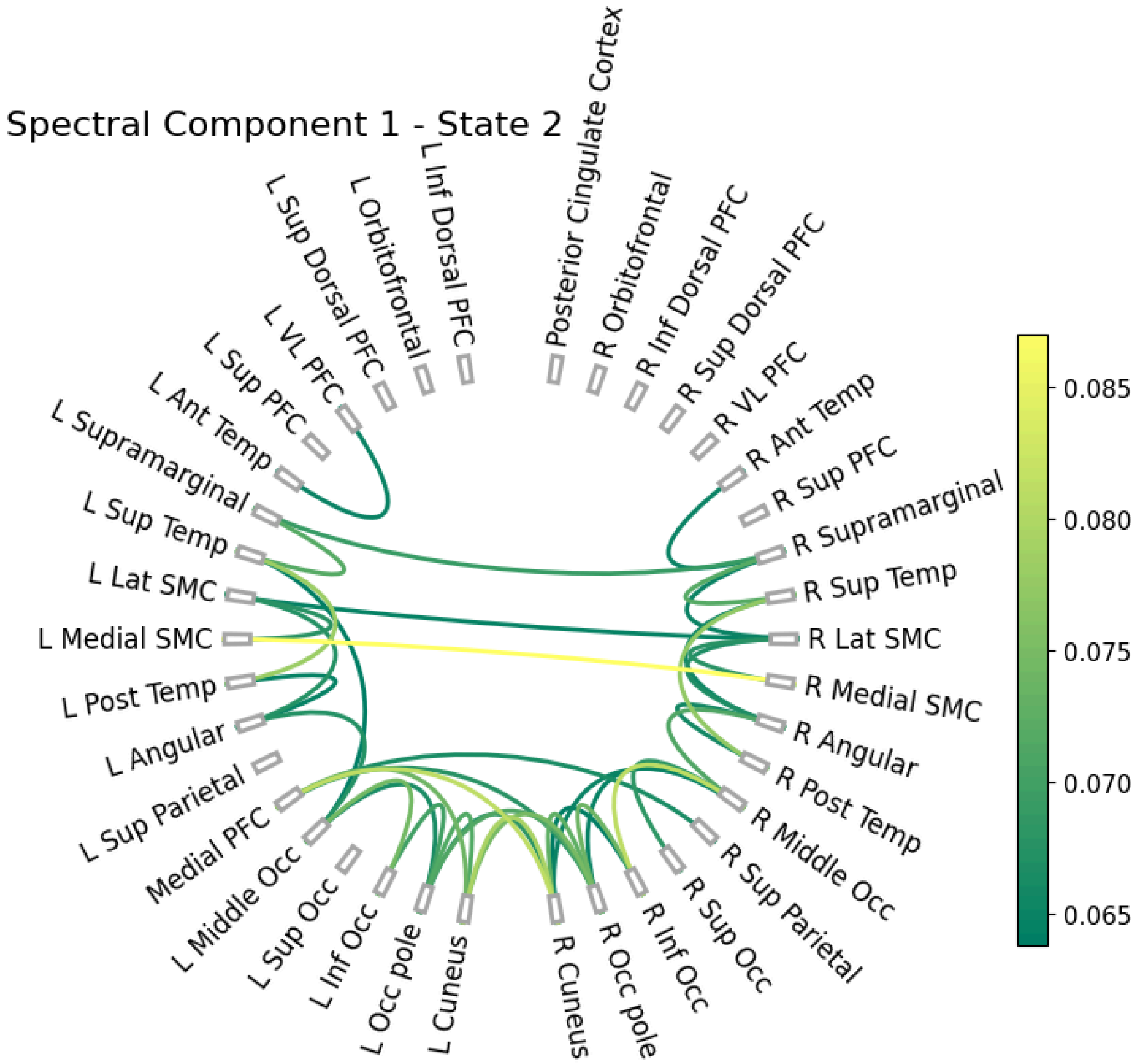
In [196…

```
connectivity_6states_SC1_S1 = thres_mean_c[0][0]  # comp 1 state 1

sc=0
title = 'Spectral Component 1 - State 1
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



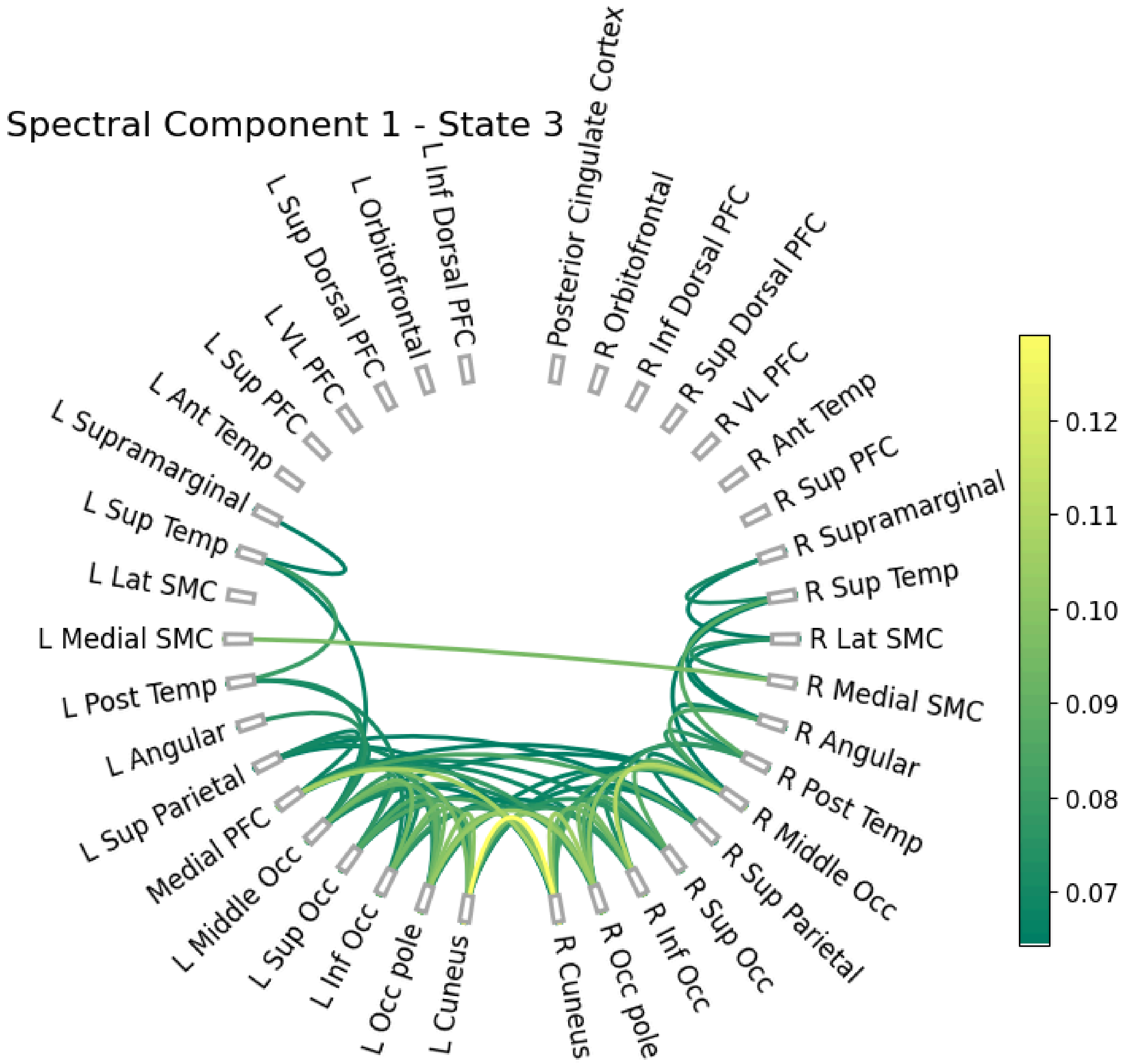
In [198…

```
connectivity_6states_SC1_S2 = thres_mean_c[0][1]  # comp 1 state 3

sc=0
title = 'Spectral Component 1 - State 2
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



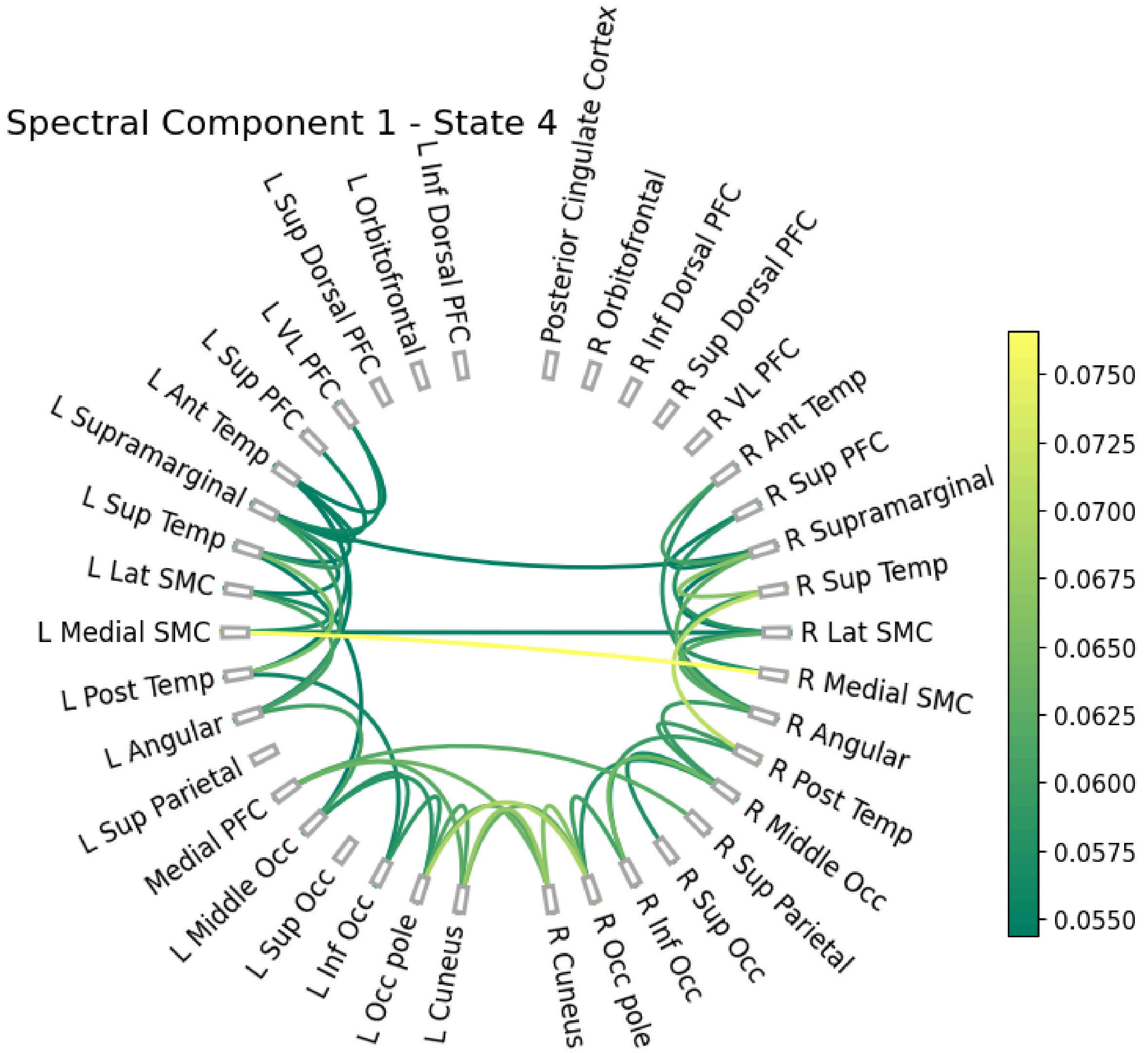
In [199…

```
connectivity_6states_SC1_S3 = thres_mean_c[0][2]  # comp 1 state 3

sc=0
title = 'Spectral Component 1 - State 3
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



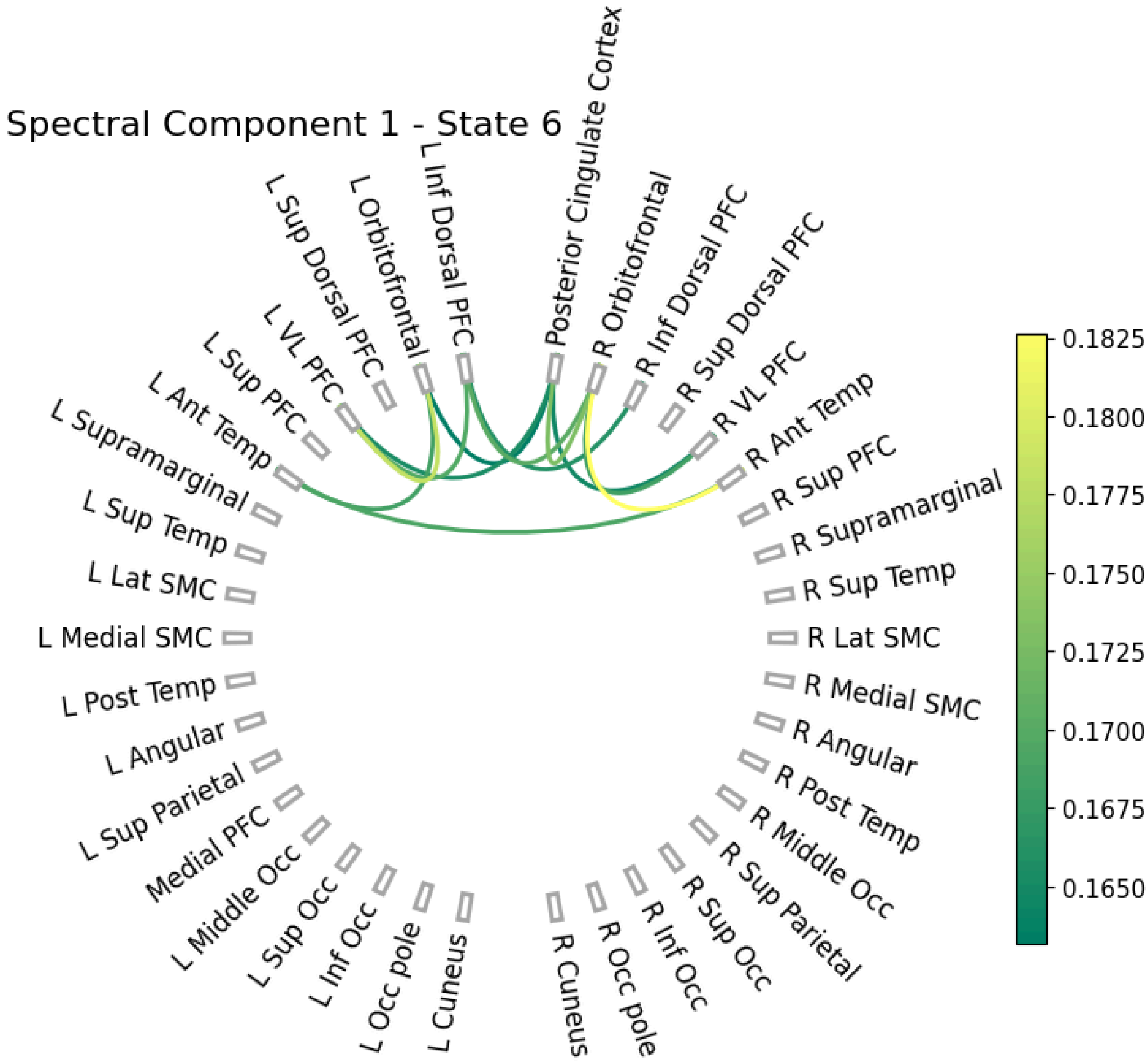
In [200…

```
connectivity_6states_SC1_S4 = thres_mean_c[0][3]   # comp 1 state 4

sc=0
title = 'Spectral Component 1 - State 4
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



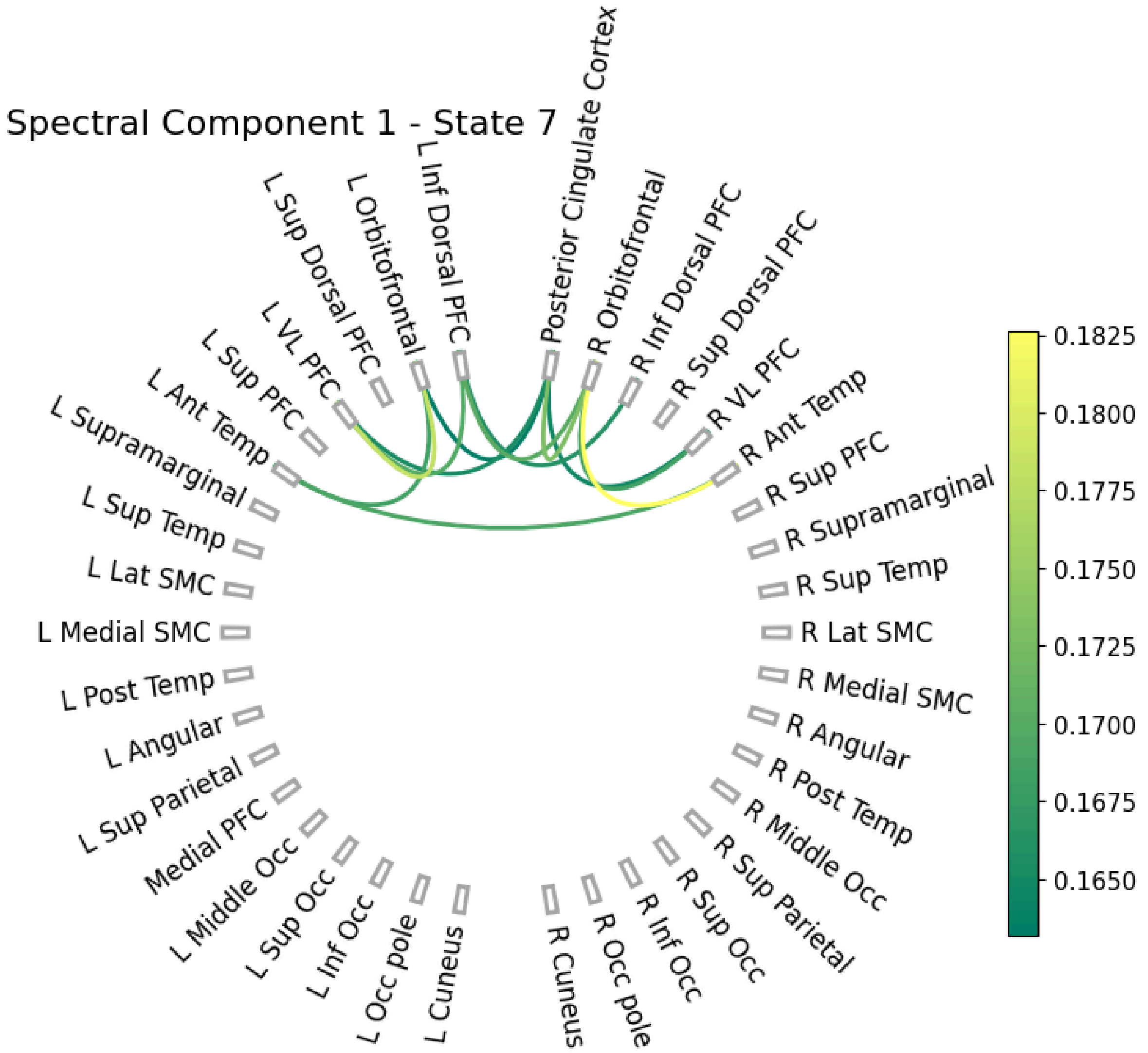
In [206…

```
connectivity_6states_SC1_S5 = thres_mean_c[0][4]   # comp 1 state 6

sc=0
title = 'Spectral Component 1 - State 6
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



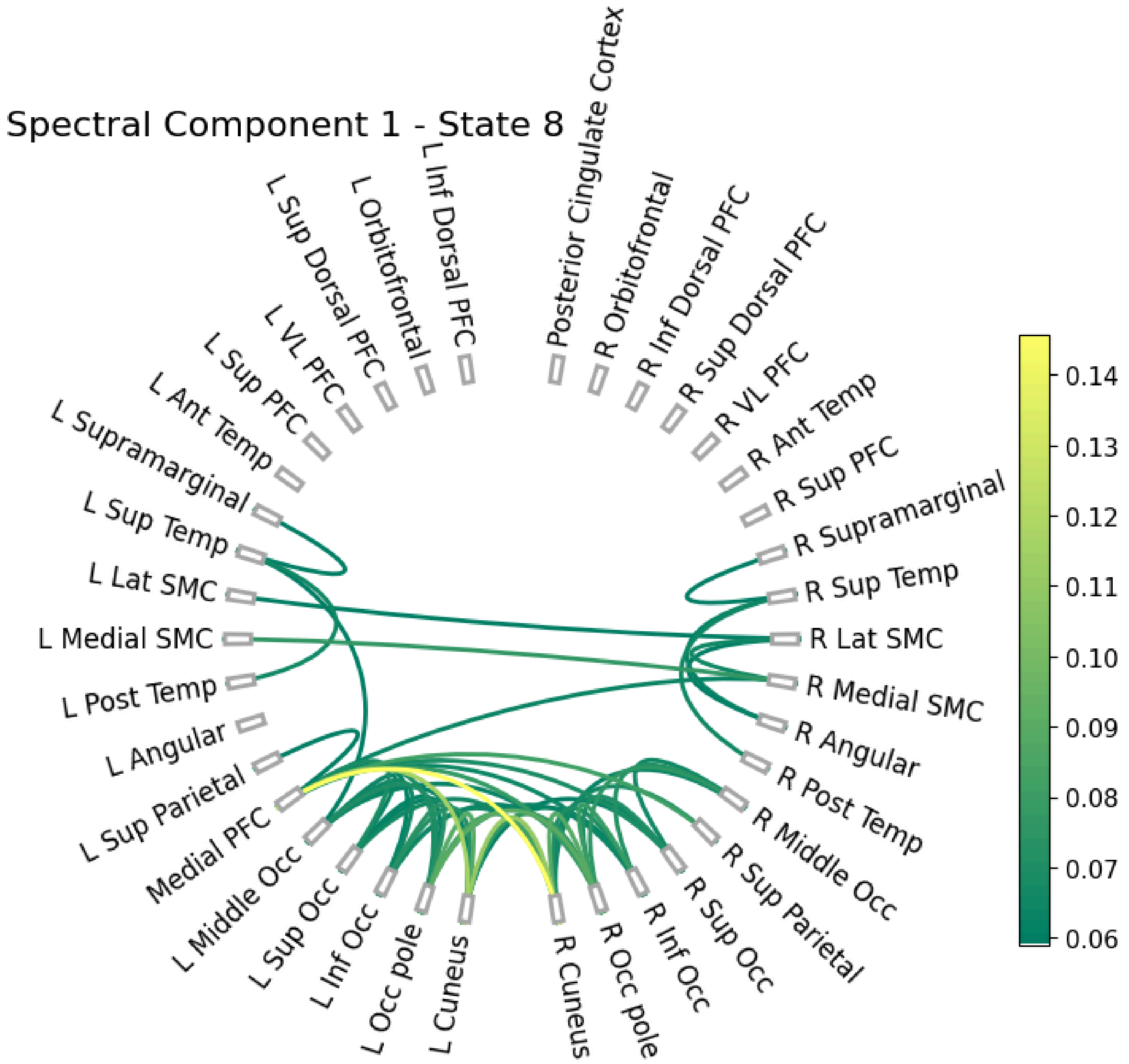
In [209…

```
connectivity_6states_SC1_S7 = thres_mean_c[0][5]  # comp 1 state 7

sc=0
title = 'Spectral Component 1 - State 7
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



In [208…

```
connectivity_6states_SC1_S8 = thres_mean_c[0][6]   # comp 1 state 8

sc=0
title = 'Spectral Component 1 - State 8
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC1_S
                              title=title, image_name=img_name, network=True
```



Spectral Component 2

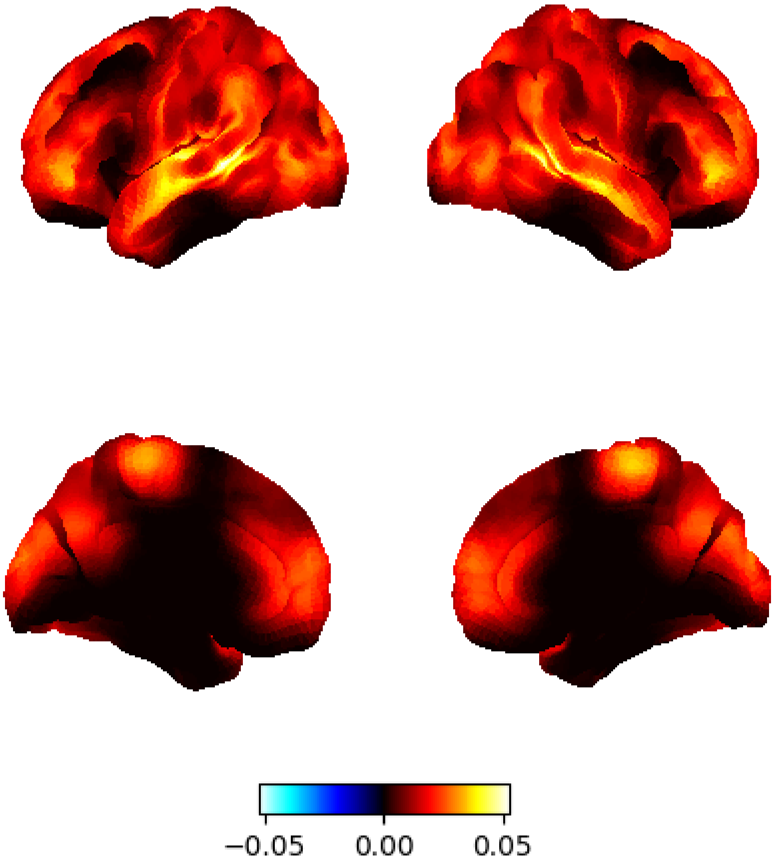
In [220…

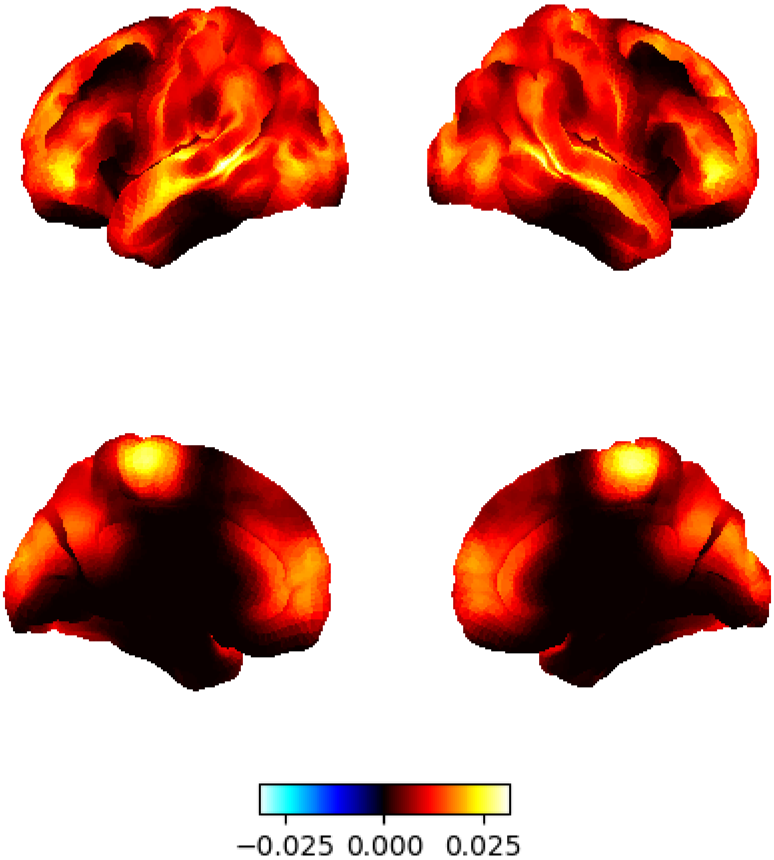
```
# Integrate the power spectra over a frequency range, weighted by the specti
p_sc_all = power.variance_from_spectra(f, gpsd, wb_comp)
p_sc2 = p_sc_all[1]
```

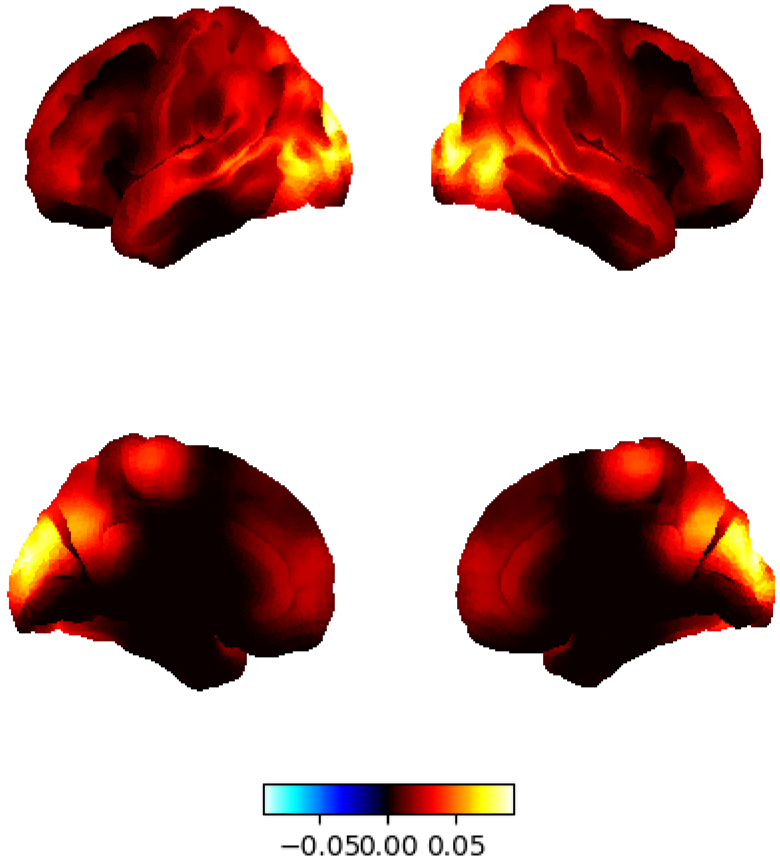
In [221…

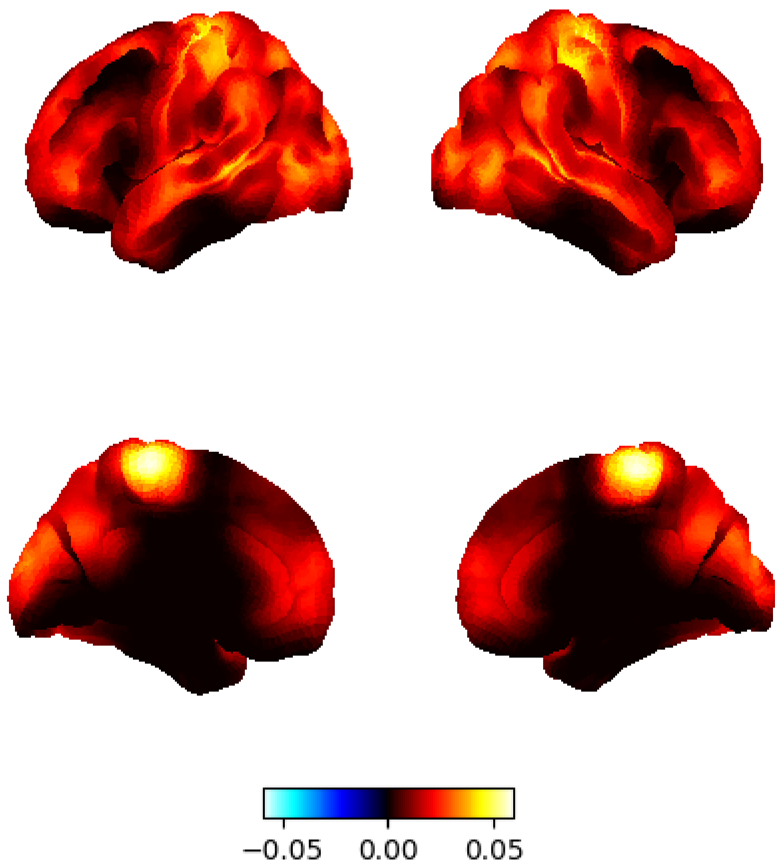
```
## Plotting power maps (averages over all subjects) per state
fig, ax = power.save(
    p_sc2,
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
)
```

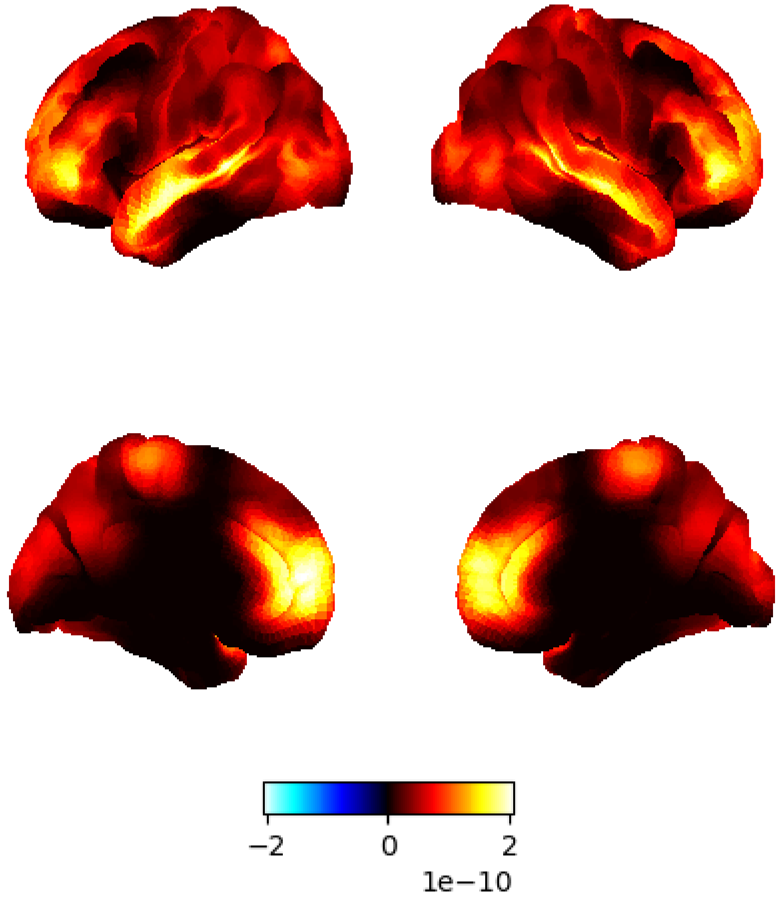
```
Saving images: 100%|██████████| 8/8 [00:07<00:00,  1.02it/s]
```

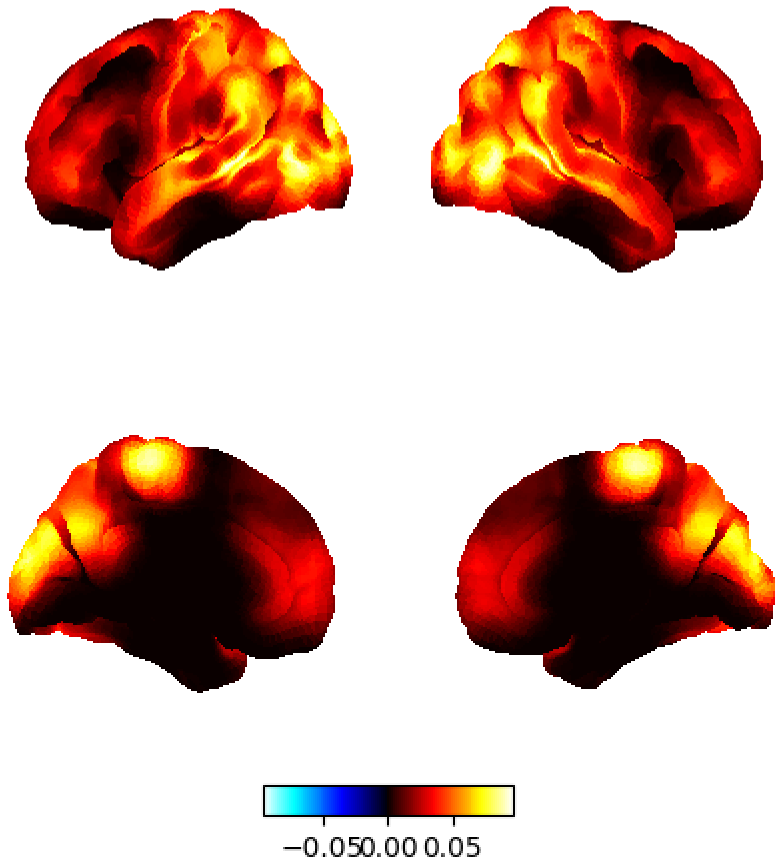

−0.05
0.00
0.05

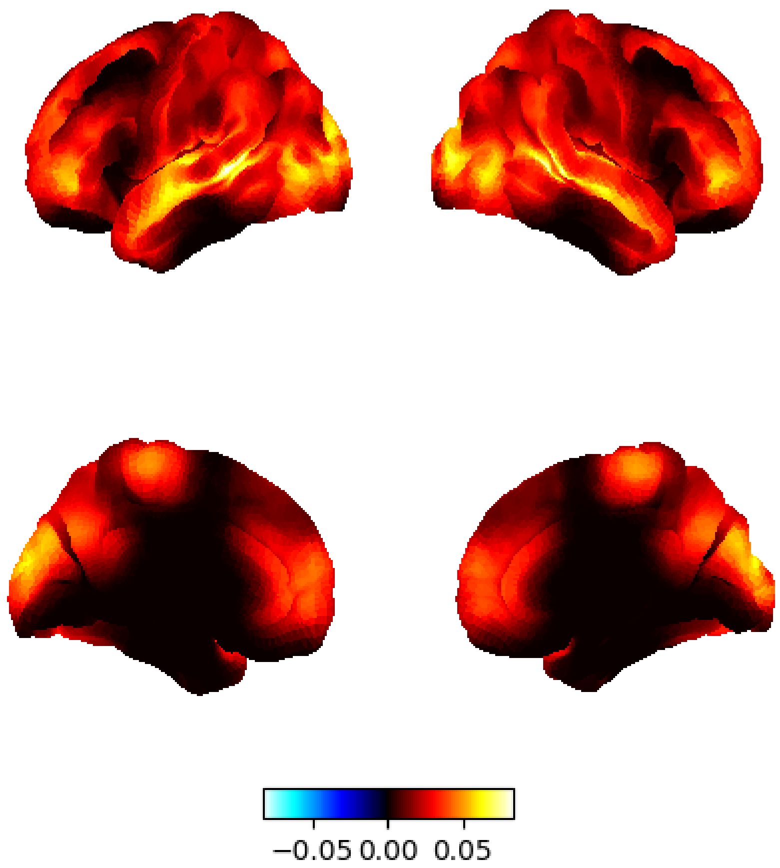

−0.025
0.000
0.025

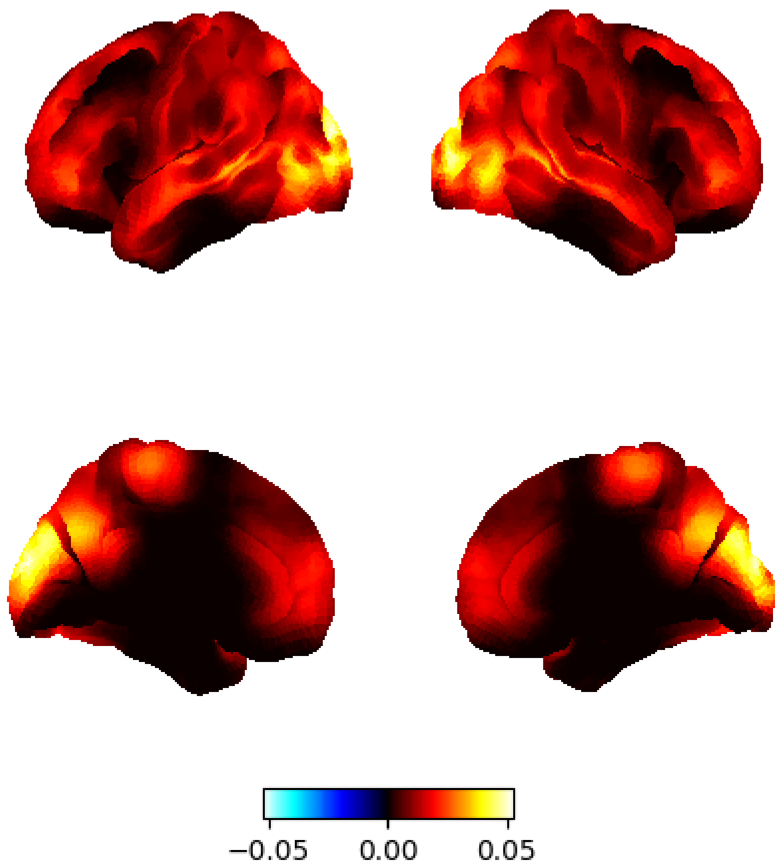

−0.050.00 0.05


−0.05
0.00
0.05


−2
0
2
1e−10


−0.05
0.00
0.05



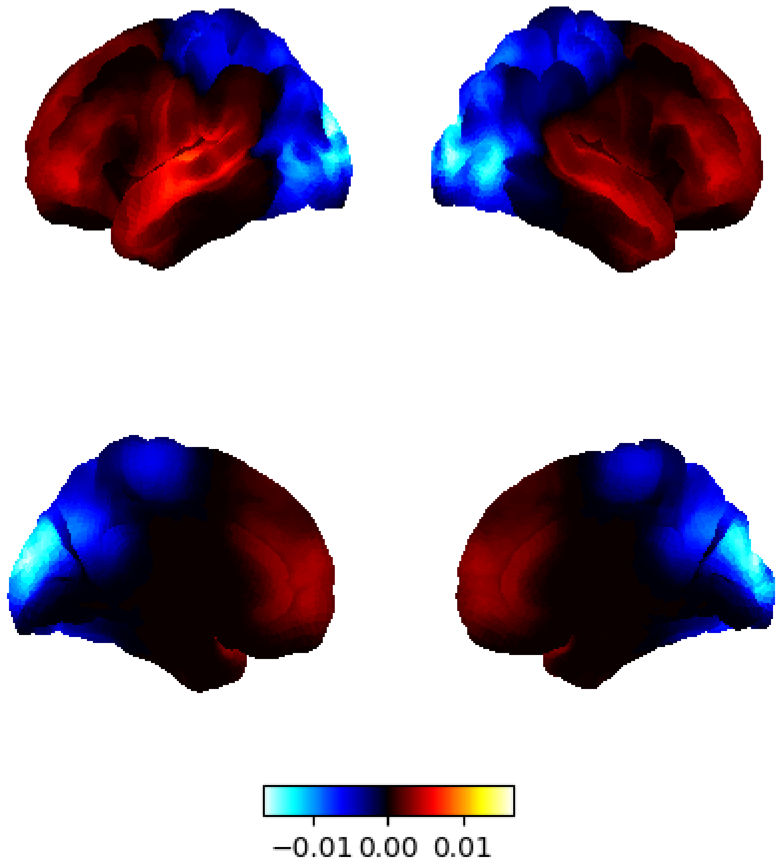


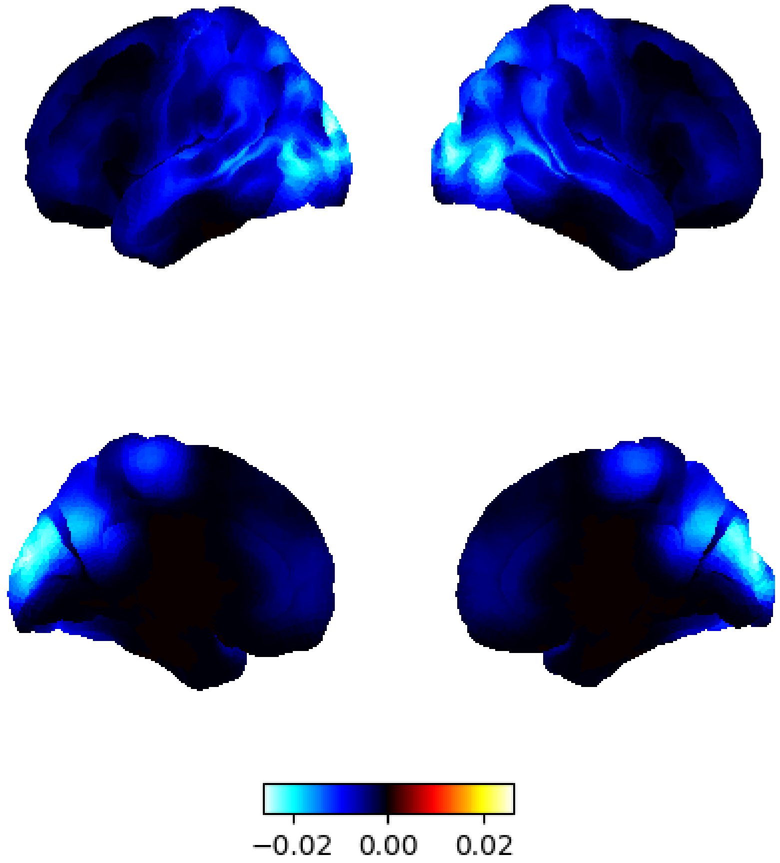
Plot **relative** to something else (by **substracting the mean**)

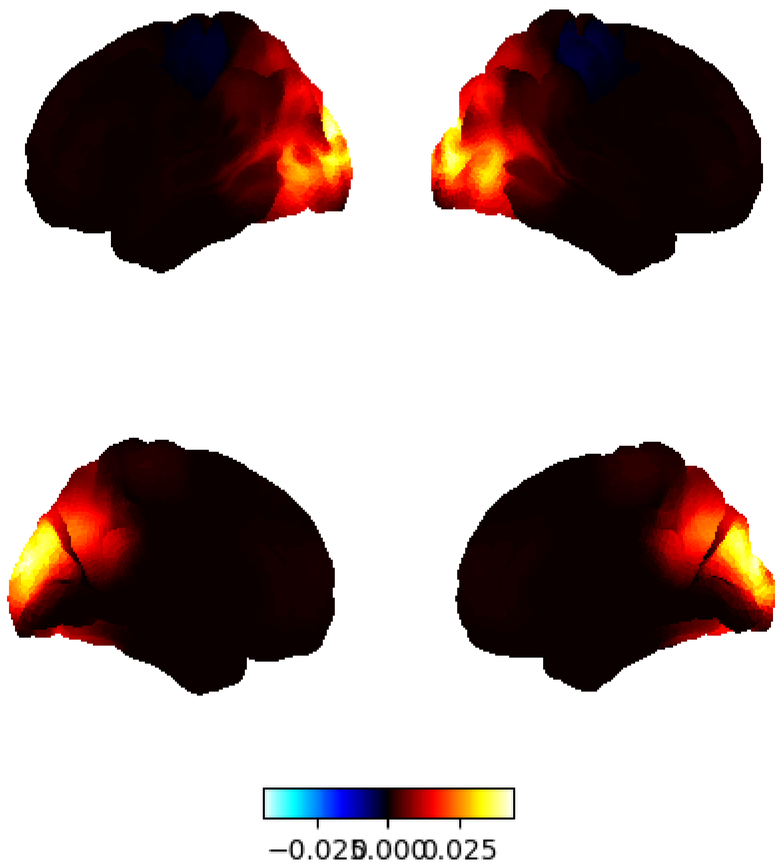
In [222…

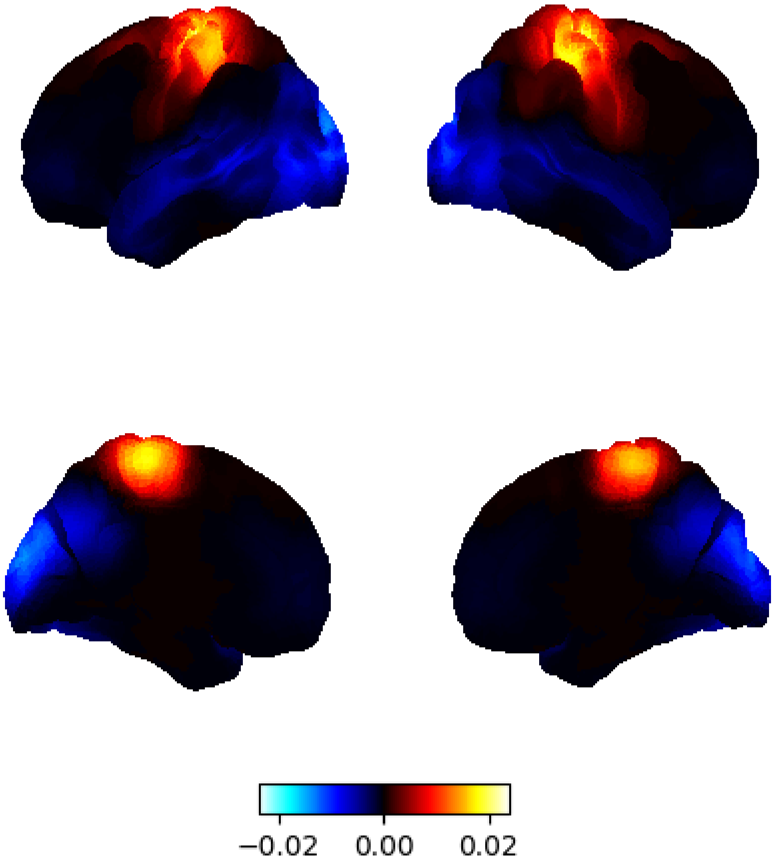
```
# Takes a few seconds for the power maps to appear
fig, ax = power.save(
    p_sc2,
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
    subtract_mean=True,
)
```

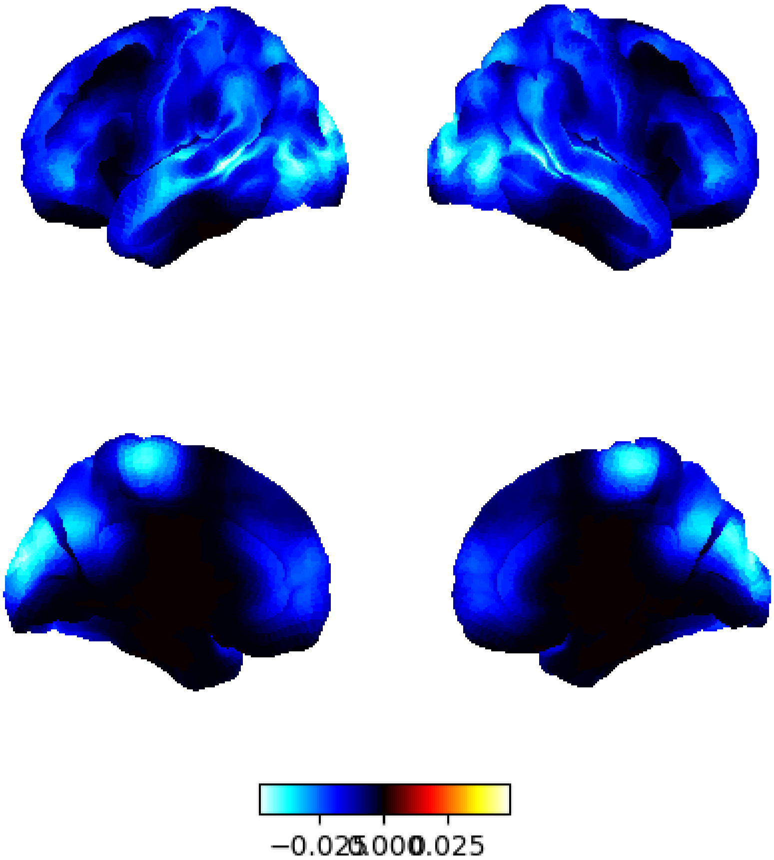
```
Saving images: 100%|██████████| 8/8 [00:08<00:00,  1.10s/it]
```

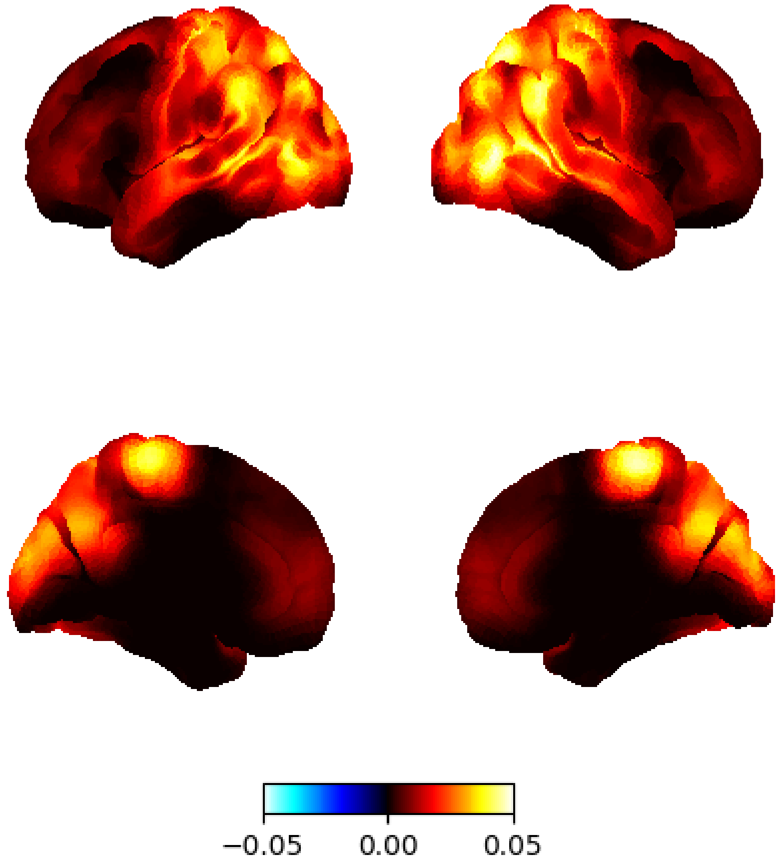


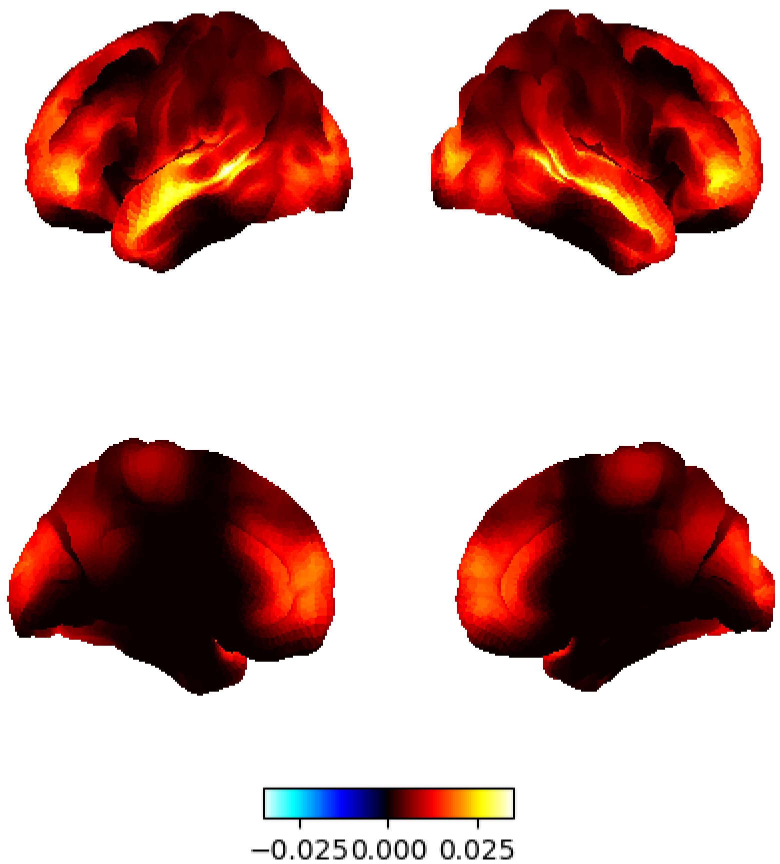

−0.02
0.00
0.02

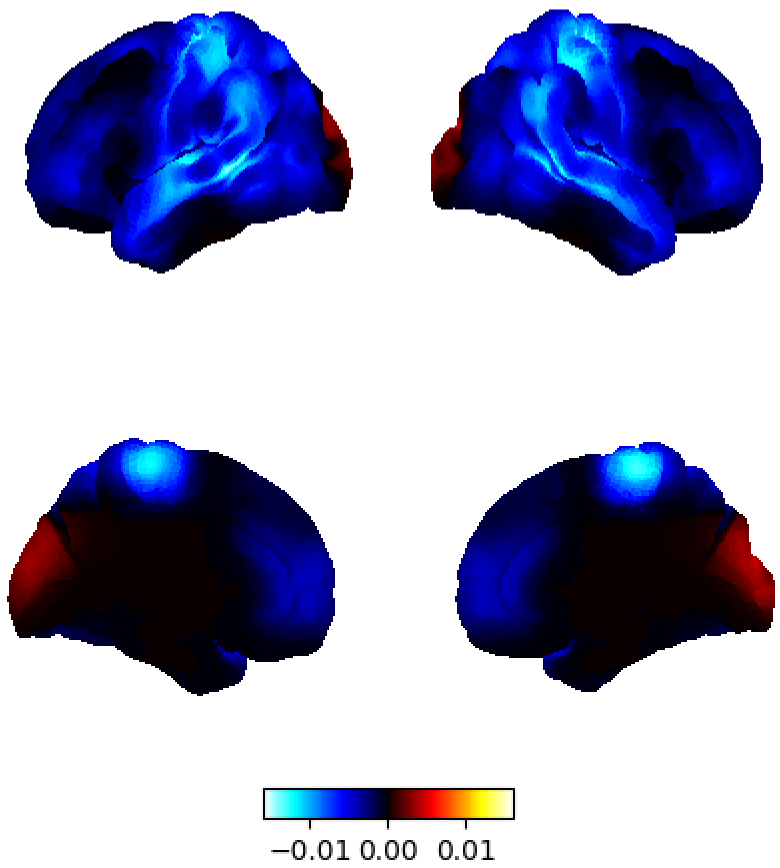

−0.025
0.000
0.025


−0.02
0.00
0.02


−0.025
0.000
0.025


−0.05
0.00
0.05


−0.025
0.000
0.025

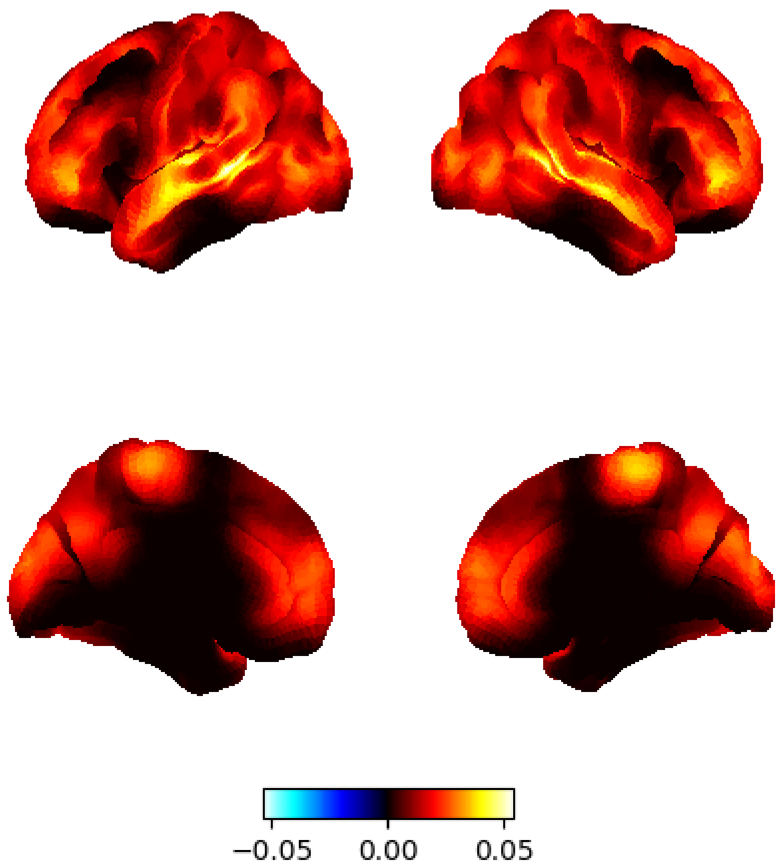


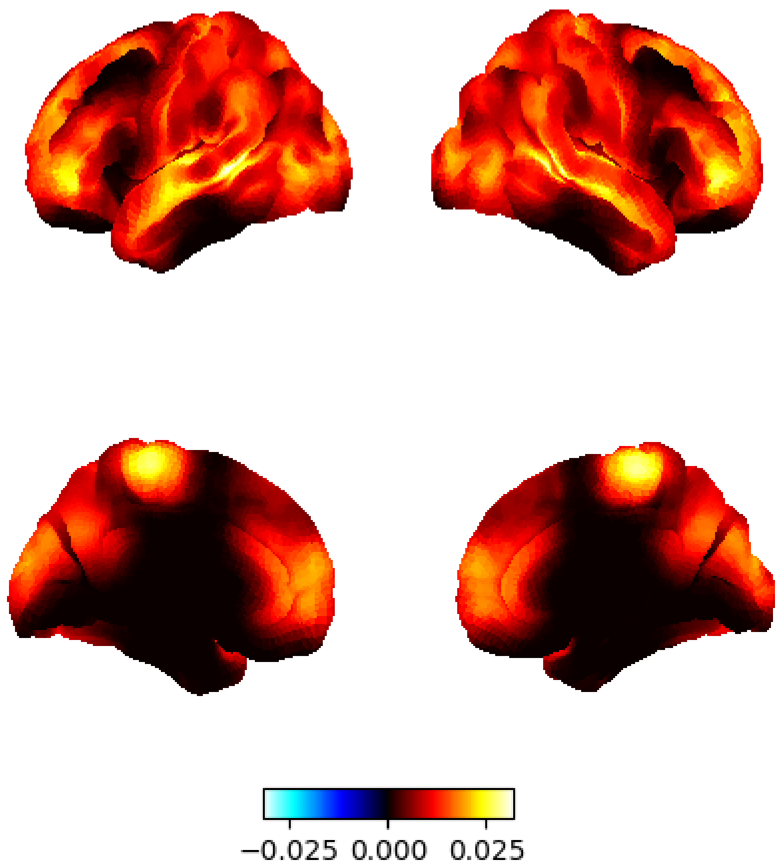
Group analysis

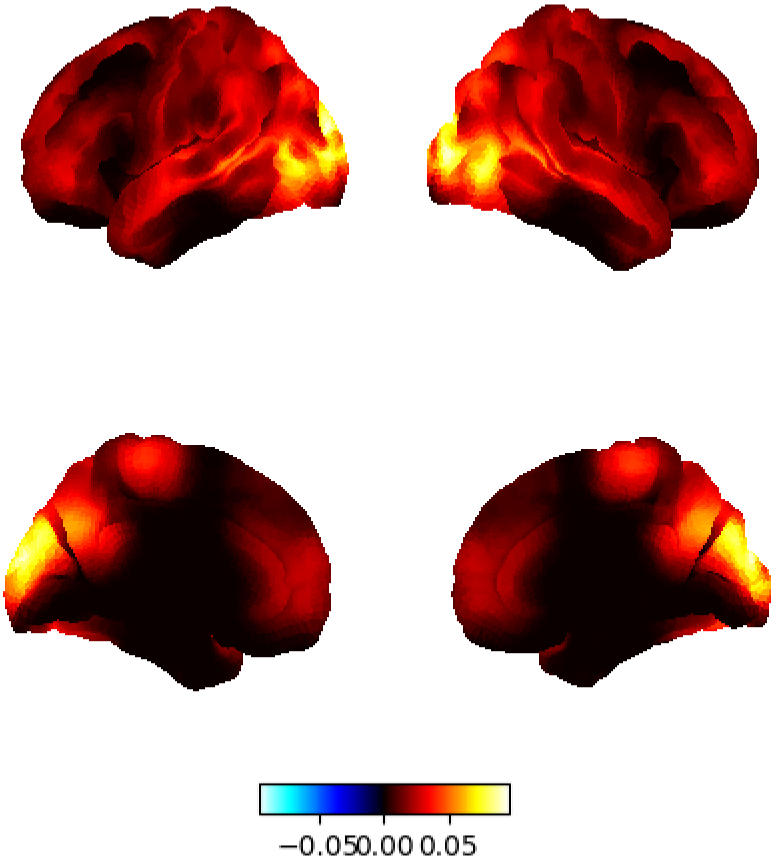
In [223…

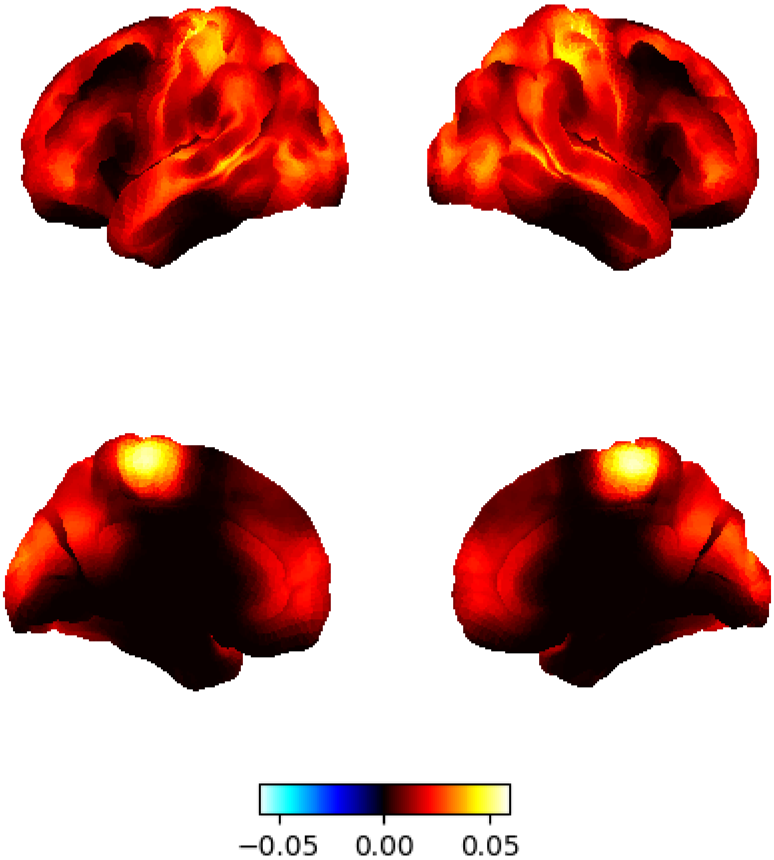
```
# Get the power arrays for group 1
p_sc2_control = power.variance_from_spectra(f, psd, wb_comp)[df_control_idx,

# Get the power arrays for group 2
p_sc2_ms = power.variance_from_spectra(f, psd, wb_comp)[df_ms_idx,1]


# Group means
p_sc2_control_mean = np.mean(p_sc2_control,axis=0)
p_sc2_ms_mean = np.mean(p_sc2_ms,axis=0)

print(np.shape(p_sc2_control))
print(np.shape(p_sc2_control_mean))

# Plot (it takes a few seconds for the brain maps to be shown)
fig, ax = power.save(
    [p_sc2_control_mean, p_sc2_ms_mean],
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
)
```

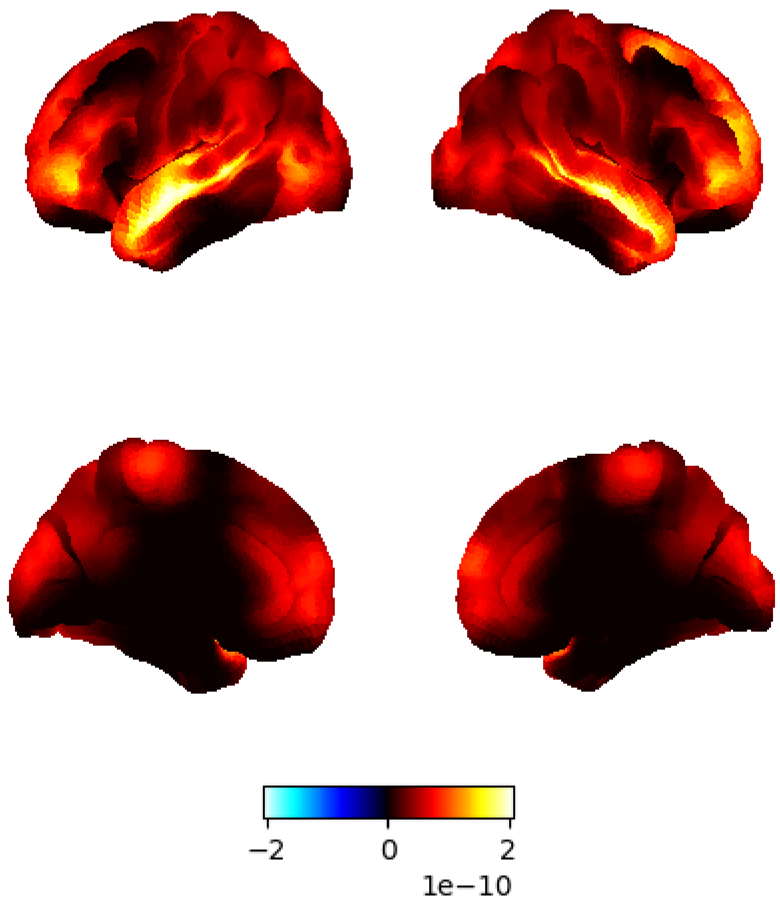
```
(37, 8, 38)
(8, 38)
Saving images: 100%|██████████| 8/8 [00:09<00:00,  1.13s/it]
```

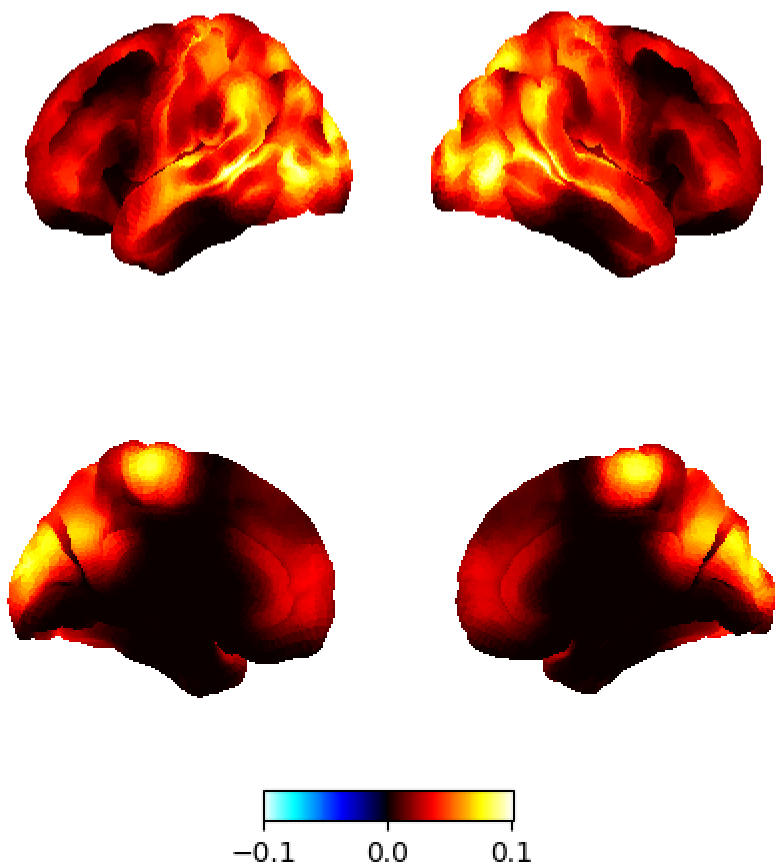

−0.05
0.00
0.05

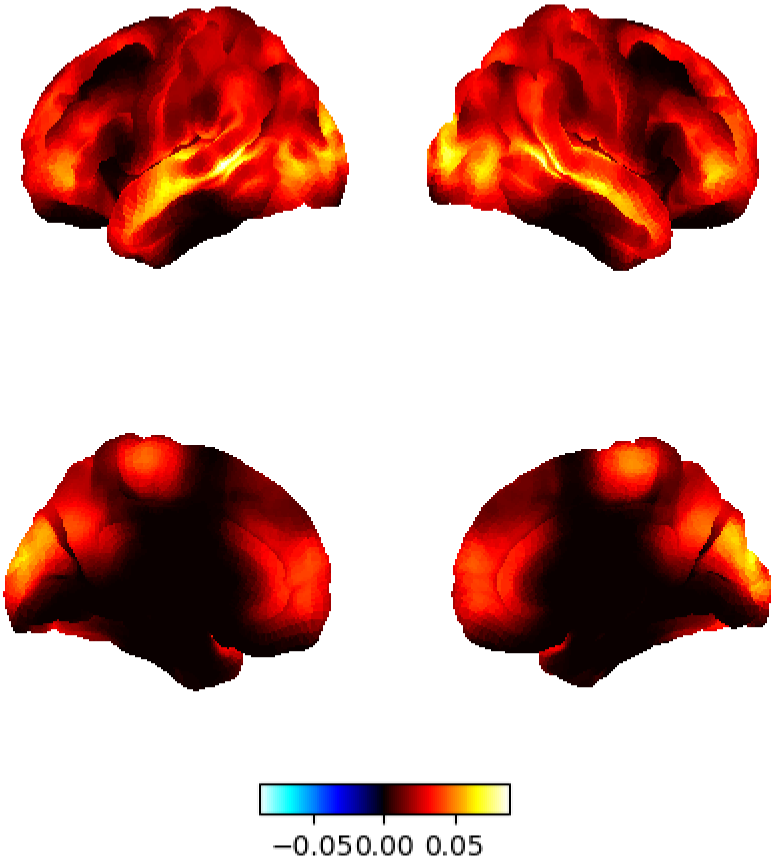

−0.025
0.000
0.025

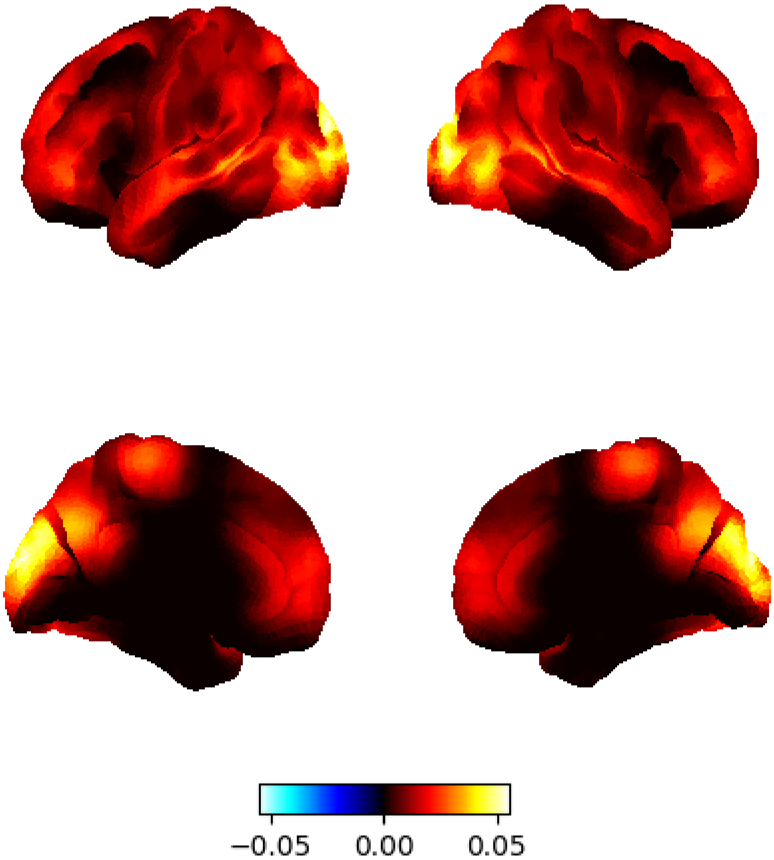

−0.05
0.00
0.05


−0.05
0.00
0.05


−2
0
2
1e−10


−0.1
0.0
0.1



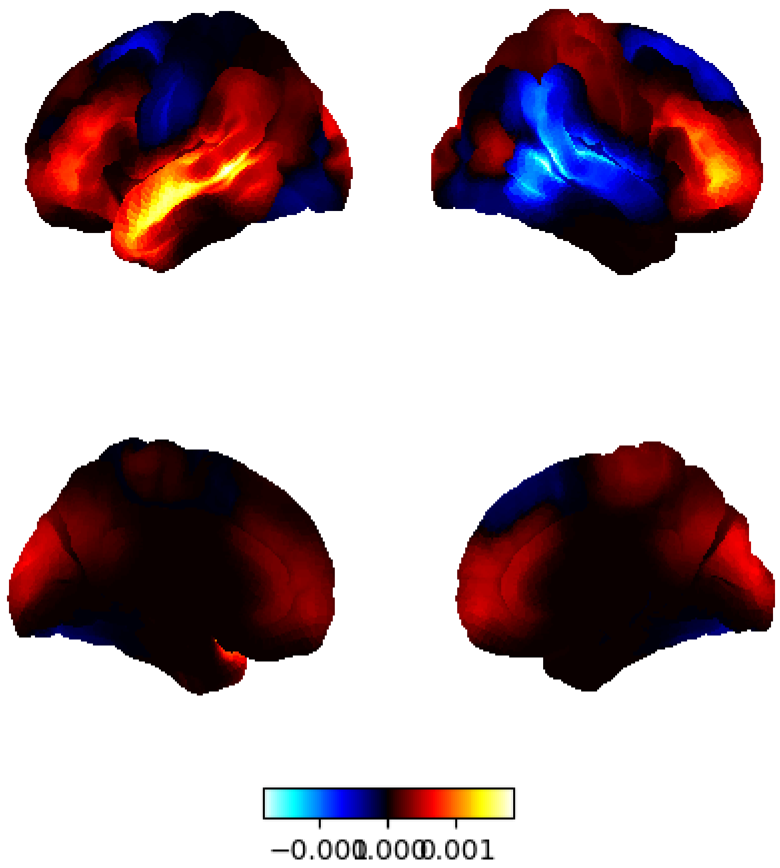


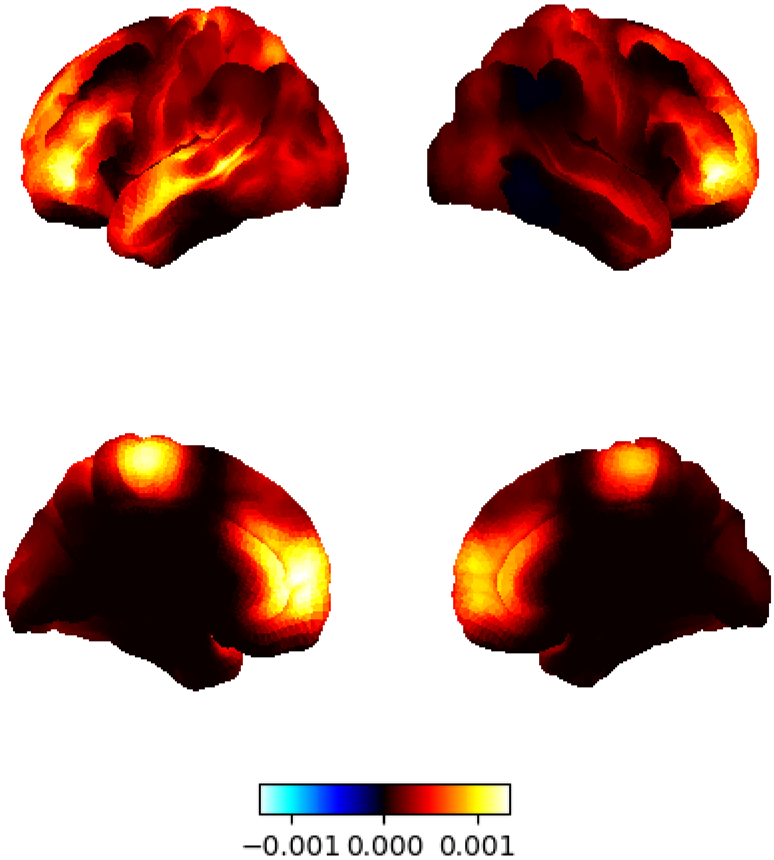
Plot the **diffference between the 2 groups**

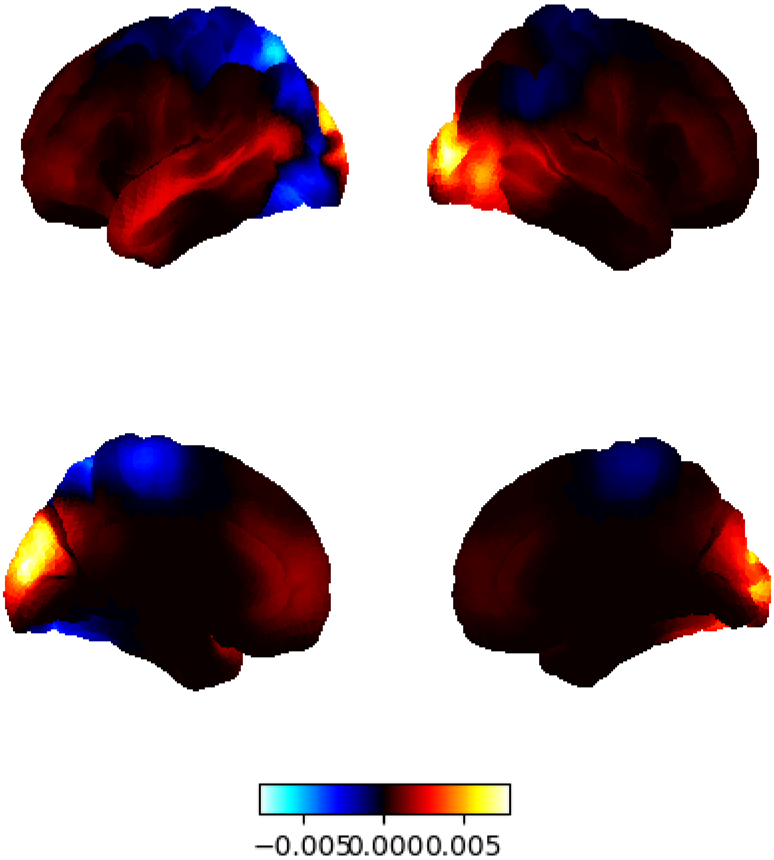
In [224…

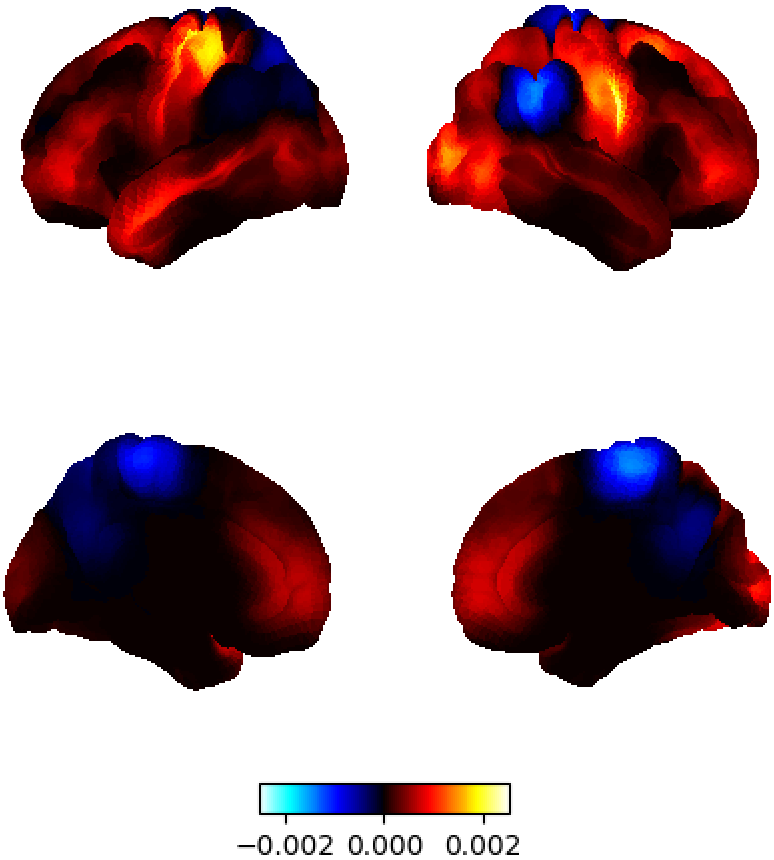
```
# Calculate the difference in power between the groups
p_diff = p_sc2_control_mean - p_sc2_ms_mean

# Plot
fig, ax = power.save(
    p_diff,
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
)
```

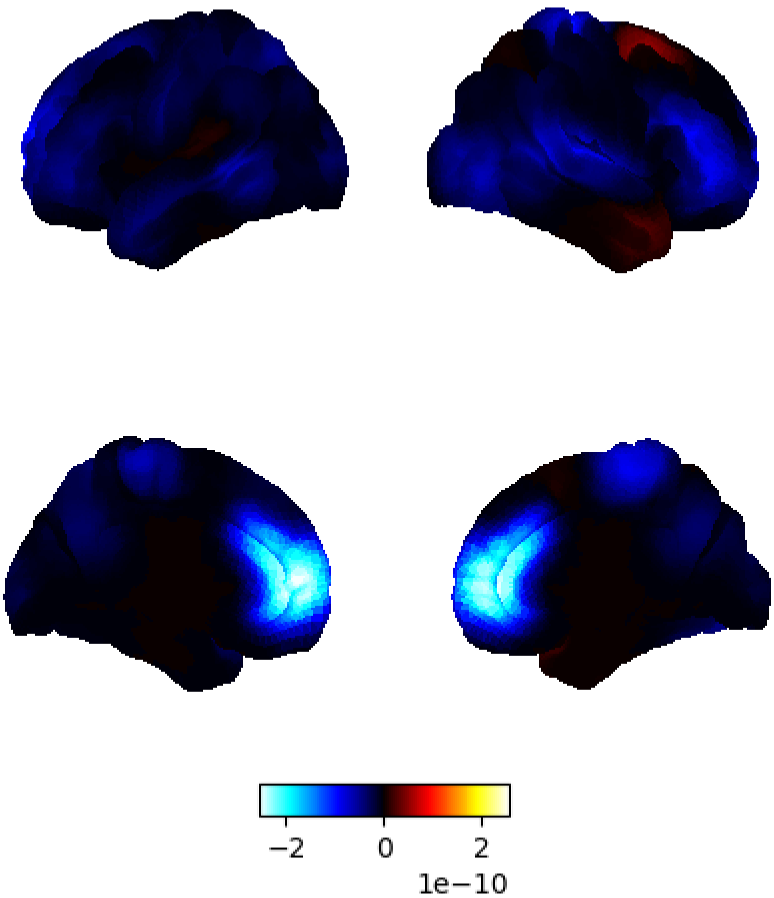
```
Saving images: 100%|██████████| 8/8 [00:08<00:00,  1.08s/it]
```

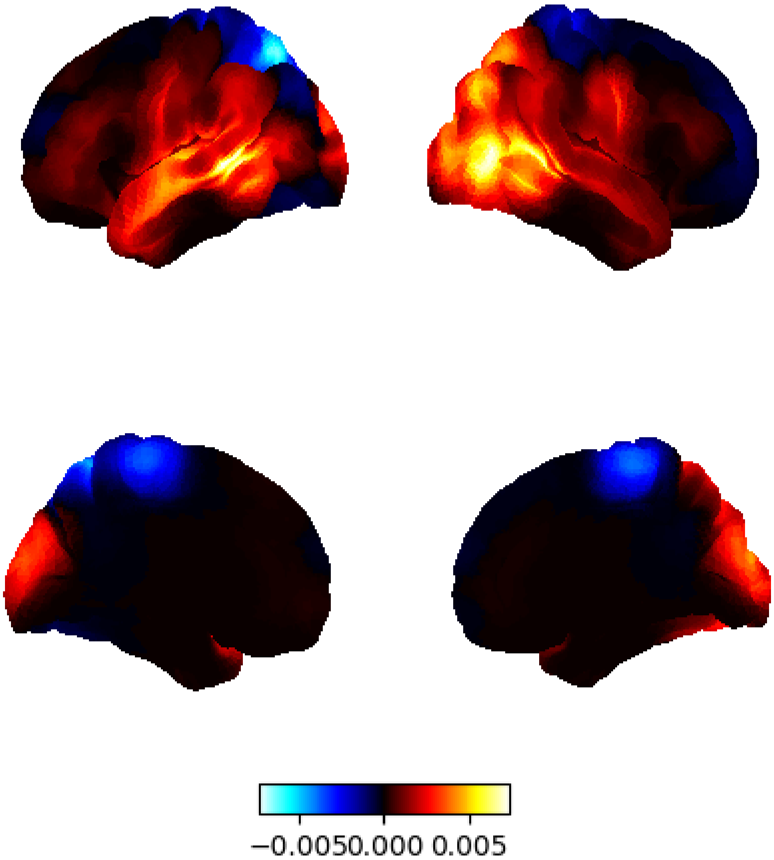


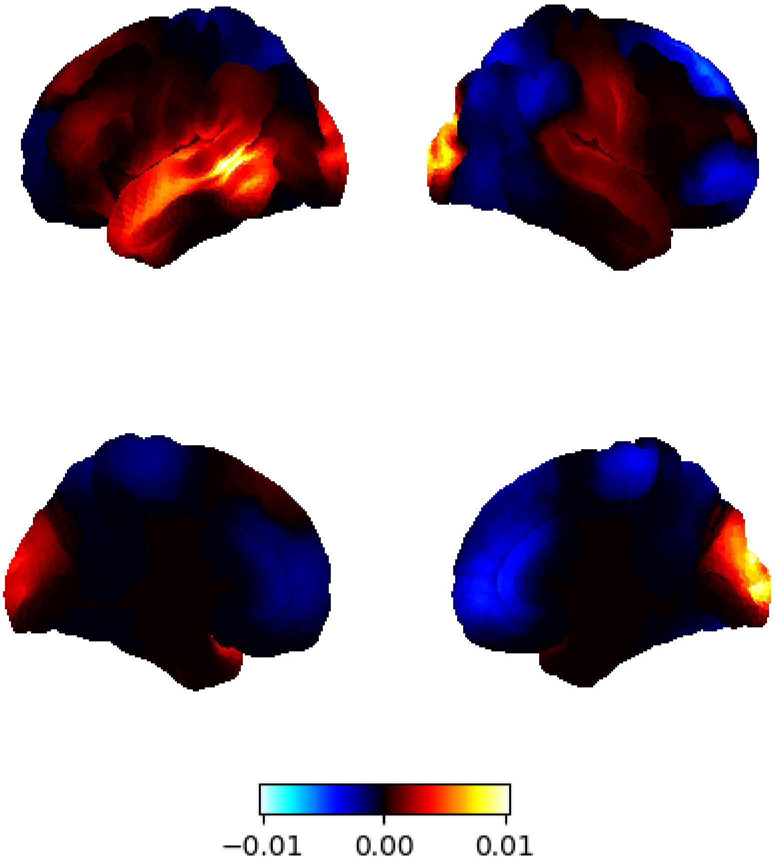

−0.001
0.000
0.001

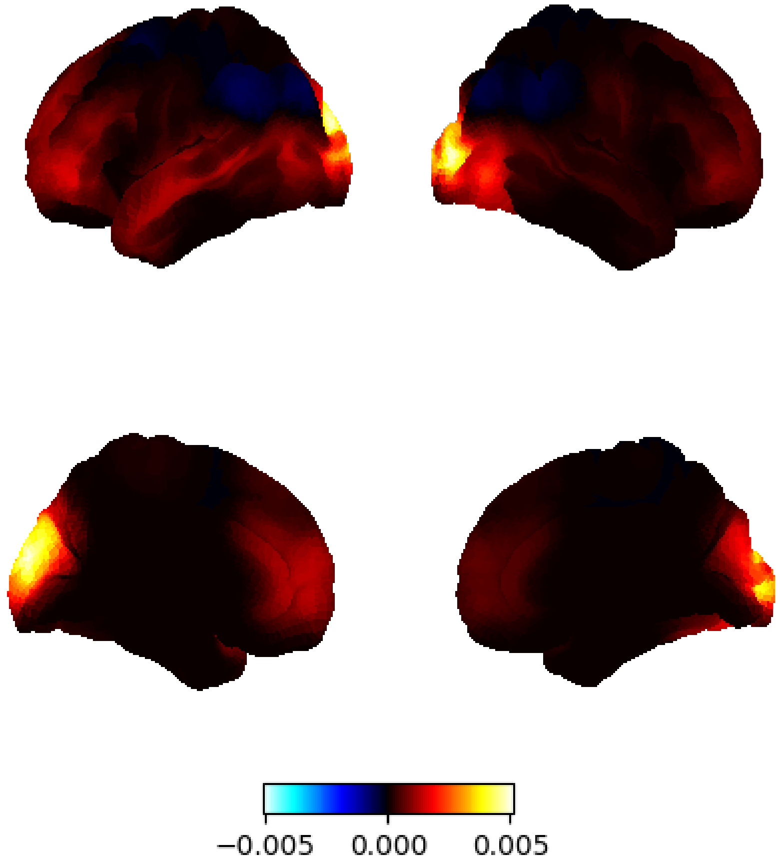

−0.005
0.000
0.005


−0.002
0.000
0.002


−2
0
2
1e−10


−0.0050.000 0.005


−0.01 0.00 0.01



Statistical significance testing

HC vs. MS

In [225…

```
from osl_dynamics.analysis import statistics

# Group assignments
## use assignments variable defined in the section of the Summary Statistics
p_sc2_gd = power.variance_from_spectra(f, psd, wb_comp)[:,1]

# Do significant testing
diff, pvalues = statistics.group_diff_max_stat_perm(
    p_sc2_gd,
    assignments,
    n_perm=500,
)

# Do we have any significant parcels?
print("Number of significant parcels:", np.sum(pvalues < 0.05))
```

```
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Differentia
l) with mode=row-shuffle
        Computing 500 permutations
        Taking max-stat across ['features 1', 'features 2'] dimensions
Using tstats as metric
Number of significant parcels: 0
```

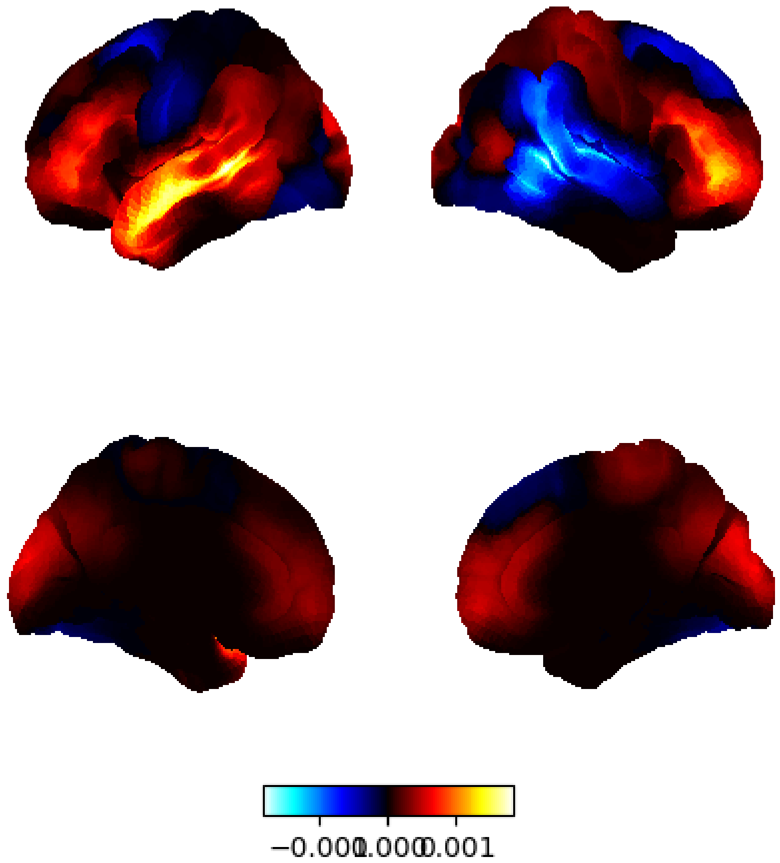
If you have parcels with a significant difference in power between groups:

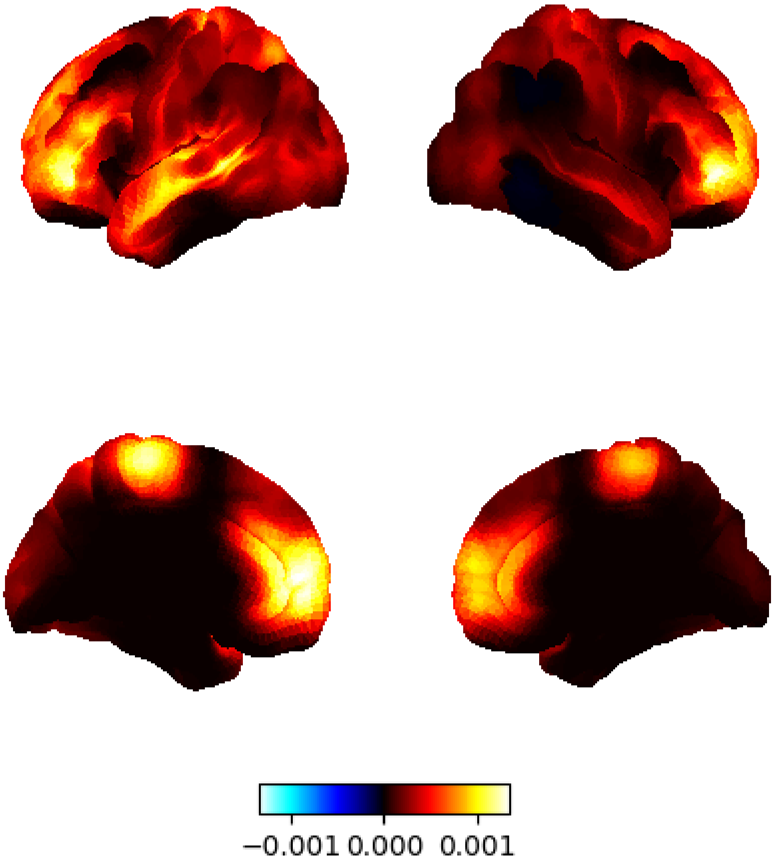
In [226…

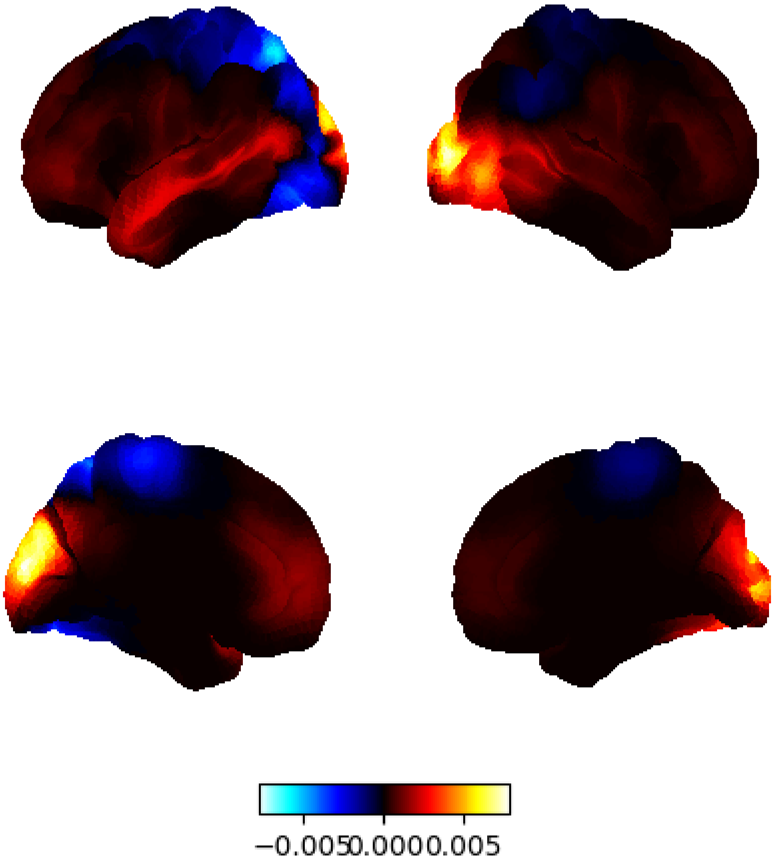
```
# Zero non-significant parcels
diff_sig = diff.copy()
```

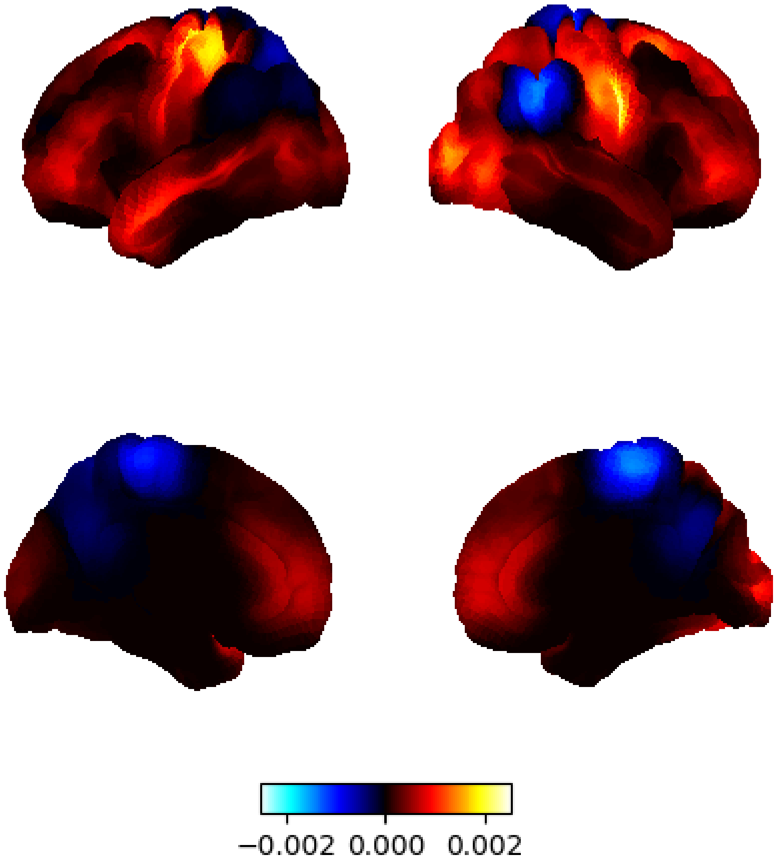
```
diff_sig[pvalues < 0.05] = 0

# Plot
fig, ax = power.save(
    diff_sig,
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
)
```

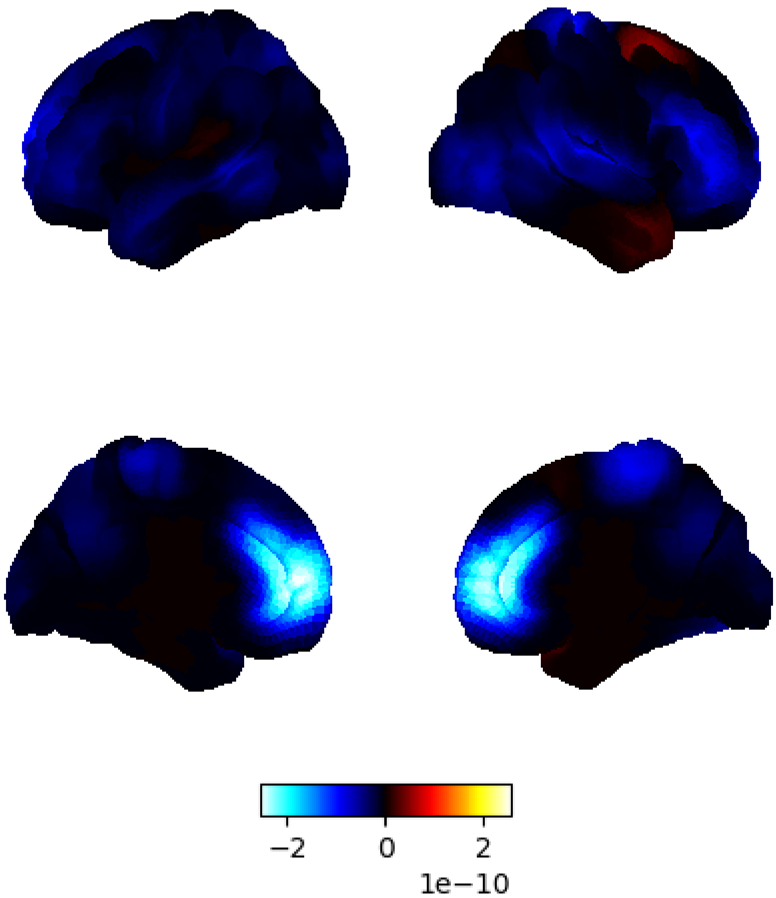
```
Saving images: 100%|██████████| 8/8 [00:08<00:00,  1.09s/it]
```

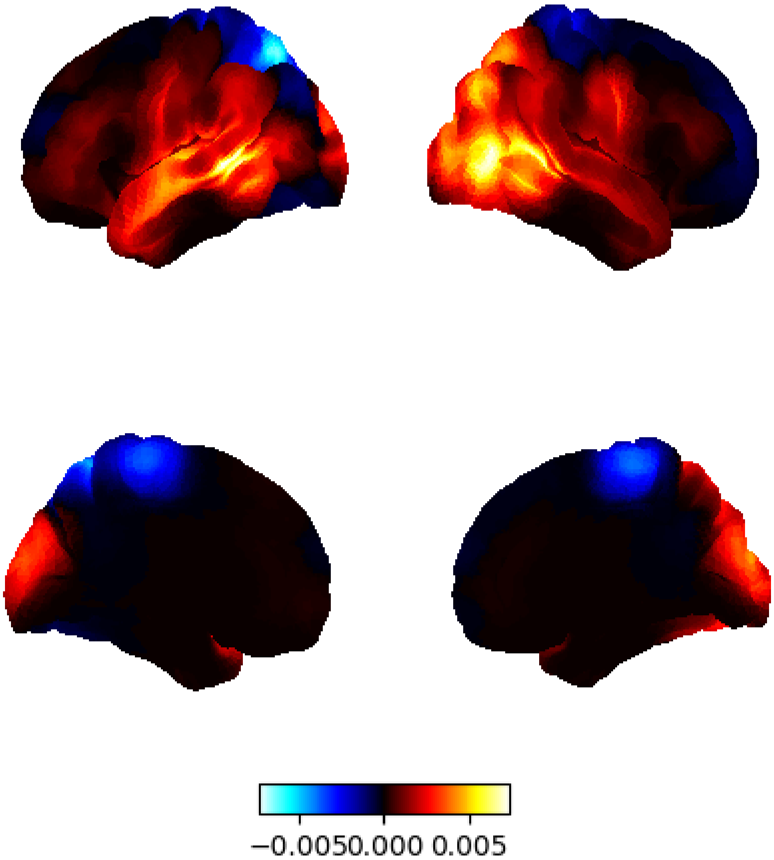


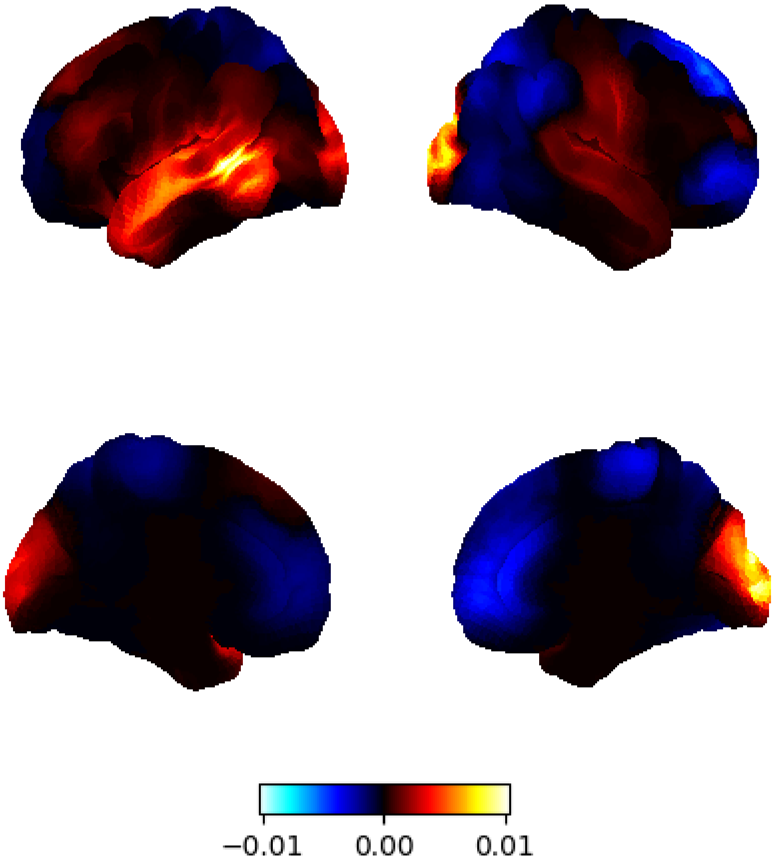

−0.001 0.000 0.001

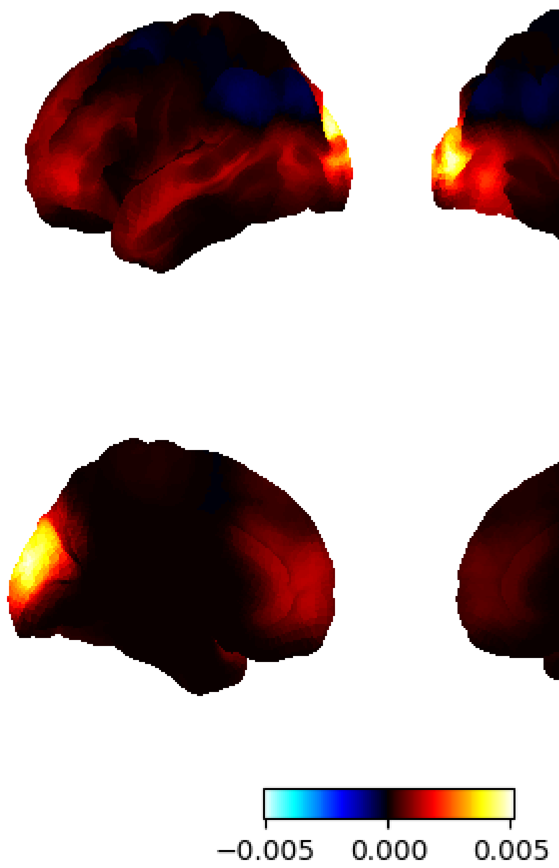

−0.0050.0000.005


−0.002
0.000
0.002


−2
0
2
1e−10


−0.0050.000 0.005


−0.01 0.00 0.01



Coherence plots

NNMF

In [297…

```
# Calculate the coherence network for each state by weighting with the spect
c = connectivity.mean_coherence_from_spectra(f, coh, wb_comp)
print(c.shape)

# Average over subjects
mean_c = np.mean(c, axis=0)
print(mean_c.shape)

# Threshold each network and look for the top 3% of connections relative to
thres_mean_c = connectivity.threshold(mean_c, percentile=98, subtract_mean=T
print(thres_mean_c.shape)
```

```
(110, 4, 8, 38, 38)
(4, 8, 38, 38)
(4, 8, 38, 38)
```

In [298…

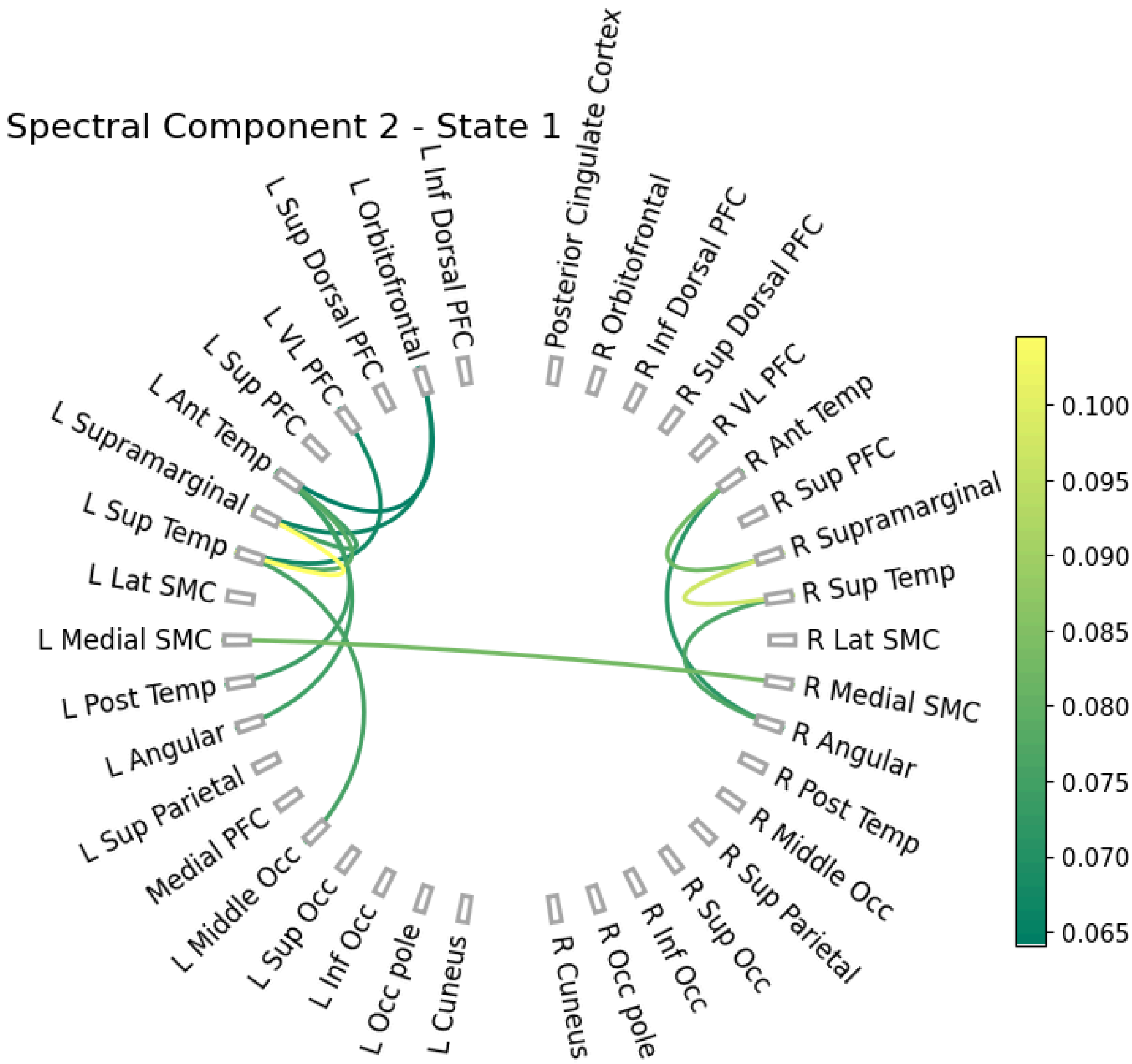
```
sc = 1
os.makedirs(model_name + "/data/Images" + "/Basic_Coherence_NNMF", exist_ok=
connectivity.save(
    thres_mean_c,
    parcellation_file="/home/olivierb/38_parcels.nii",
    component=sc, #1st spectral component
    filename=model_name + "/data/Images/Basic_Coherence_NNMF/coh_Spectral_Co
)
```

```
Saving images: 100%|██████████| 8/8 [00:09<00:00,  1.23s/it]
```

Thresholded 2%

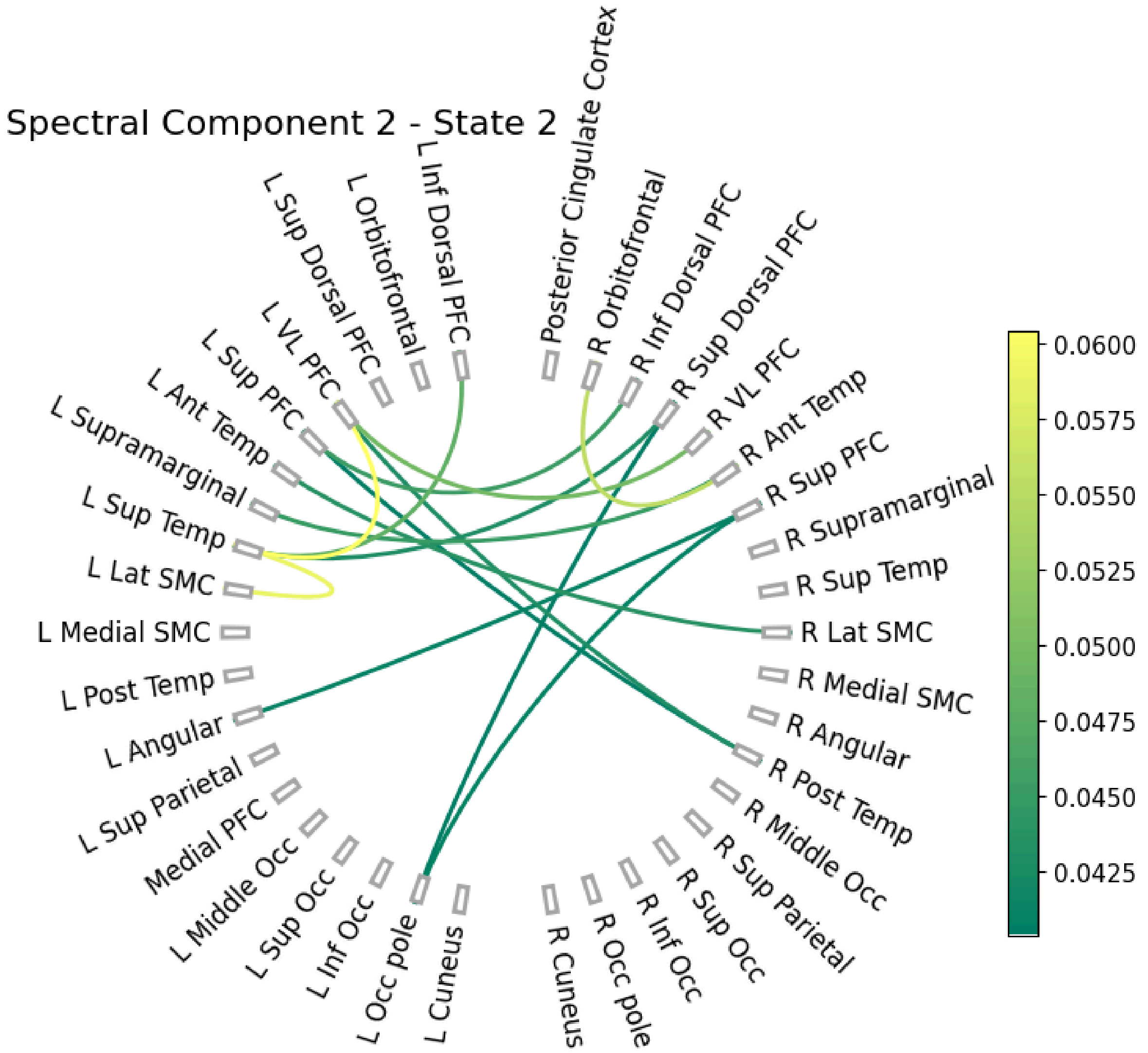
In [229…

```
connectivity_6states_SC2 = thres_mean_c[1]
connectivity_6states_SC2_S1 = connectivity_6states_SC2[0]

sc=1
title = 'Spectral Component 2 - State 1
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



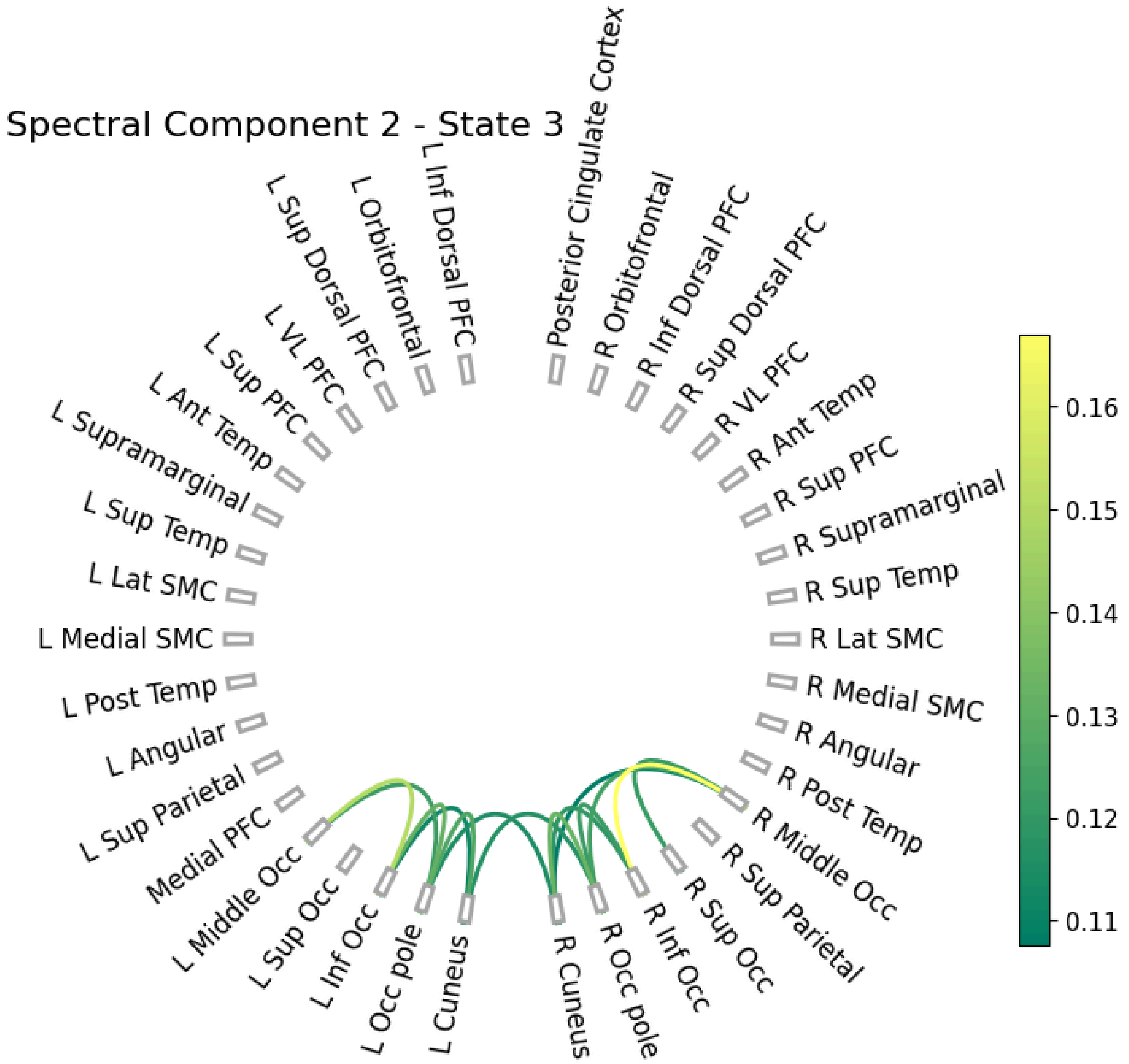
In [230…

```
connectivity_6states_SC2_S2 = connectivity_6states_SC2[1]

sc=1
title = 'Spectral Component 2 - State 2
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



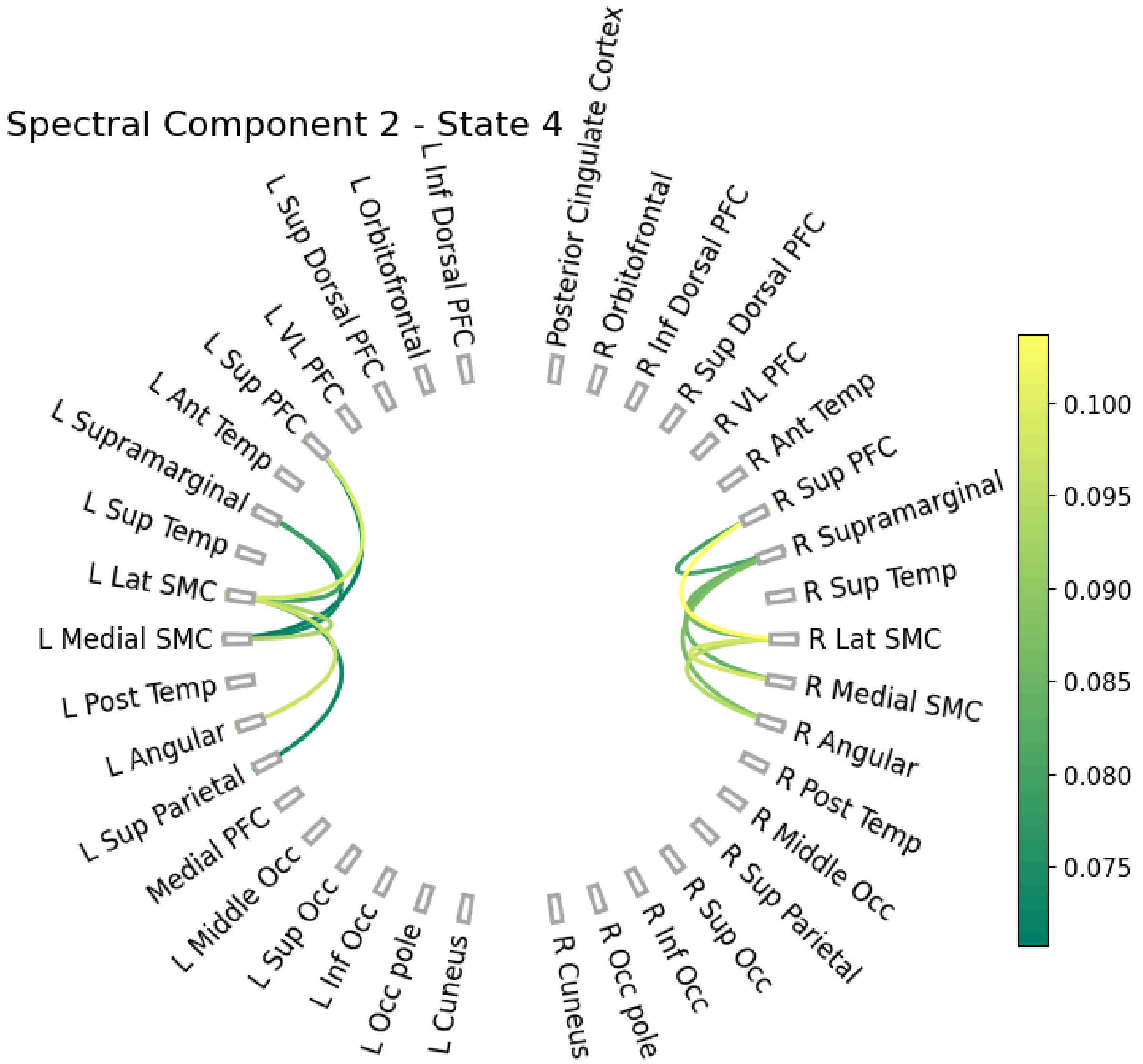
In [231…

```
connectivity_6states_SC2_S3 = connectivity_6states_SC2[2]

sc=1
title = 'Spectral Component 2 - State 3
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



In [232…

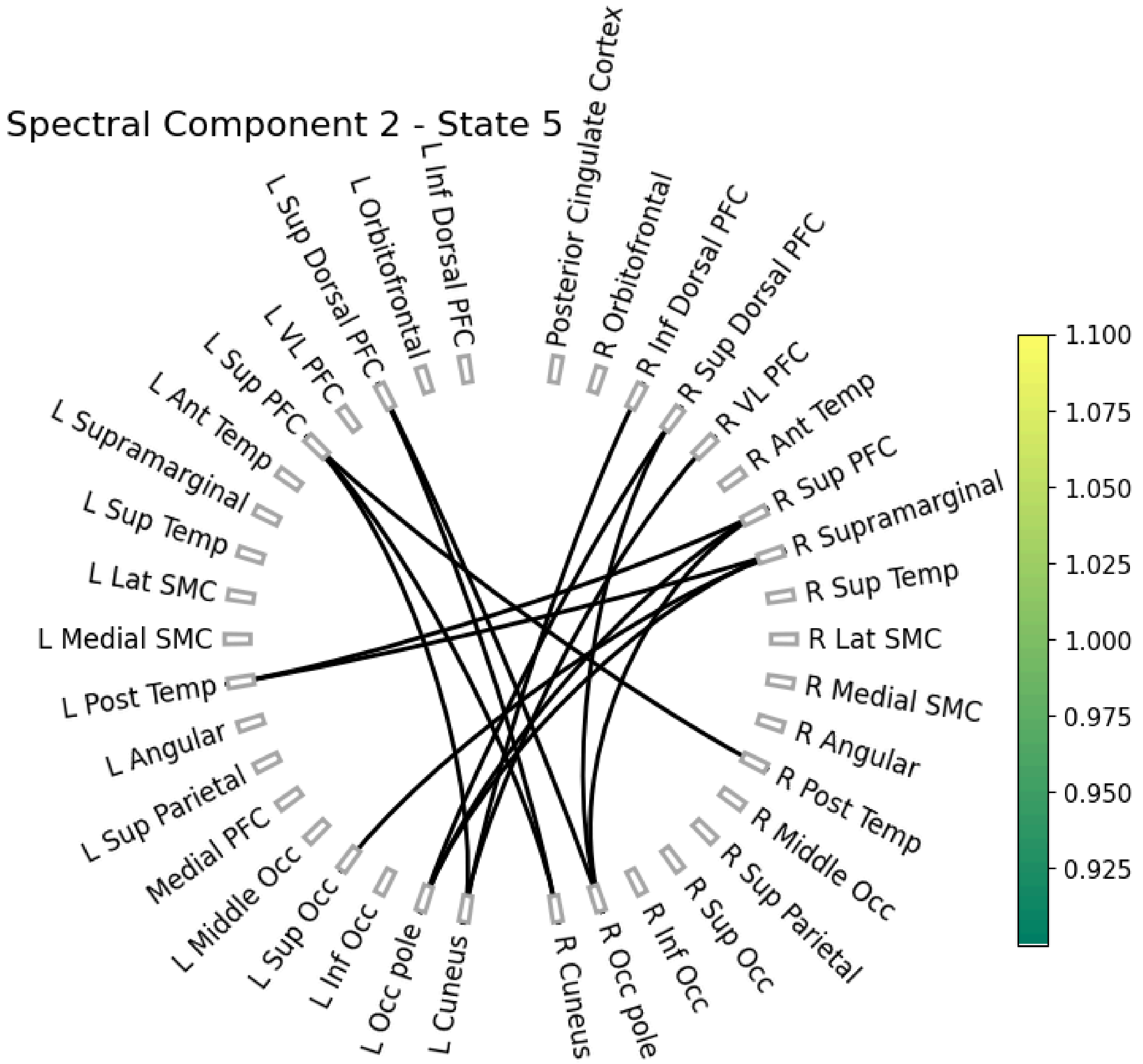
```
connectivity_6states_SC2_S4 = connectivity_6states_SC2[3]

sc=1
title = 'Spectral Component 2 - State 4
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



In [233…

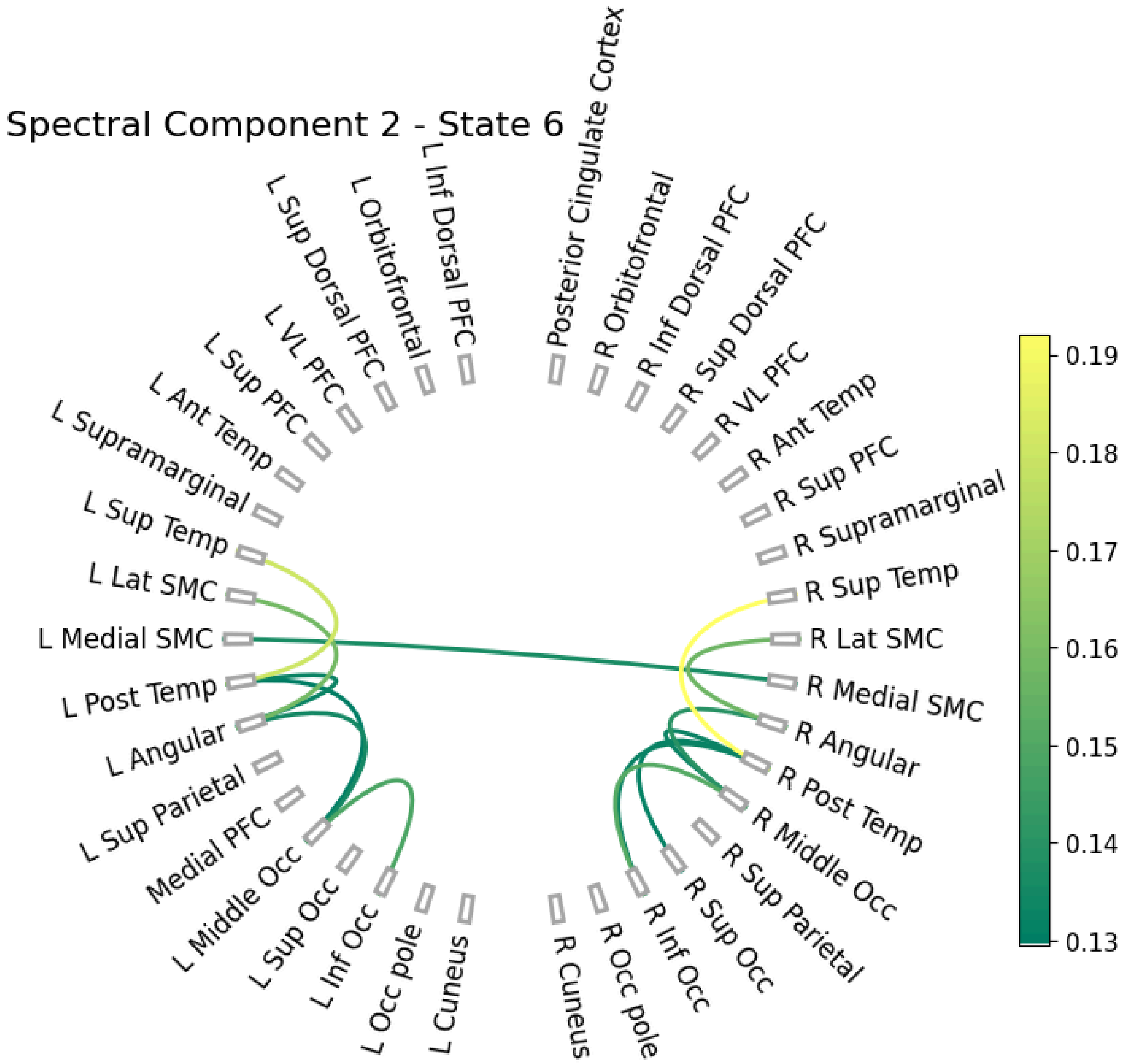
```
connectivity_6states_SC2_S5 = connectivity_6states_SC2[4]

sc=1
title = 'Spectral Component 2 - State 5
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```

```
/home/olivierb/.local/lib/python3.9/site-packages/mne/viz/circle.py:289:
RuntimeWarning: invalid value encountered in divide
  con_val_scaled = (con - vmin) / vrange
```



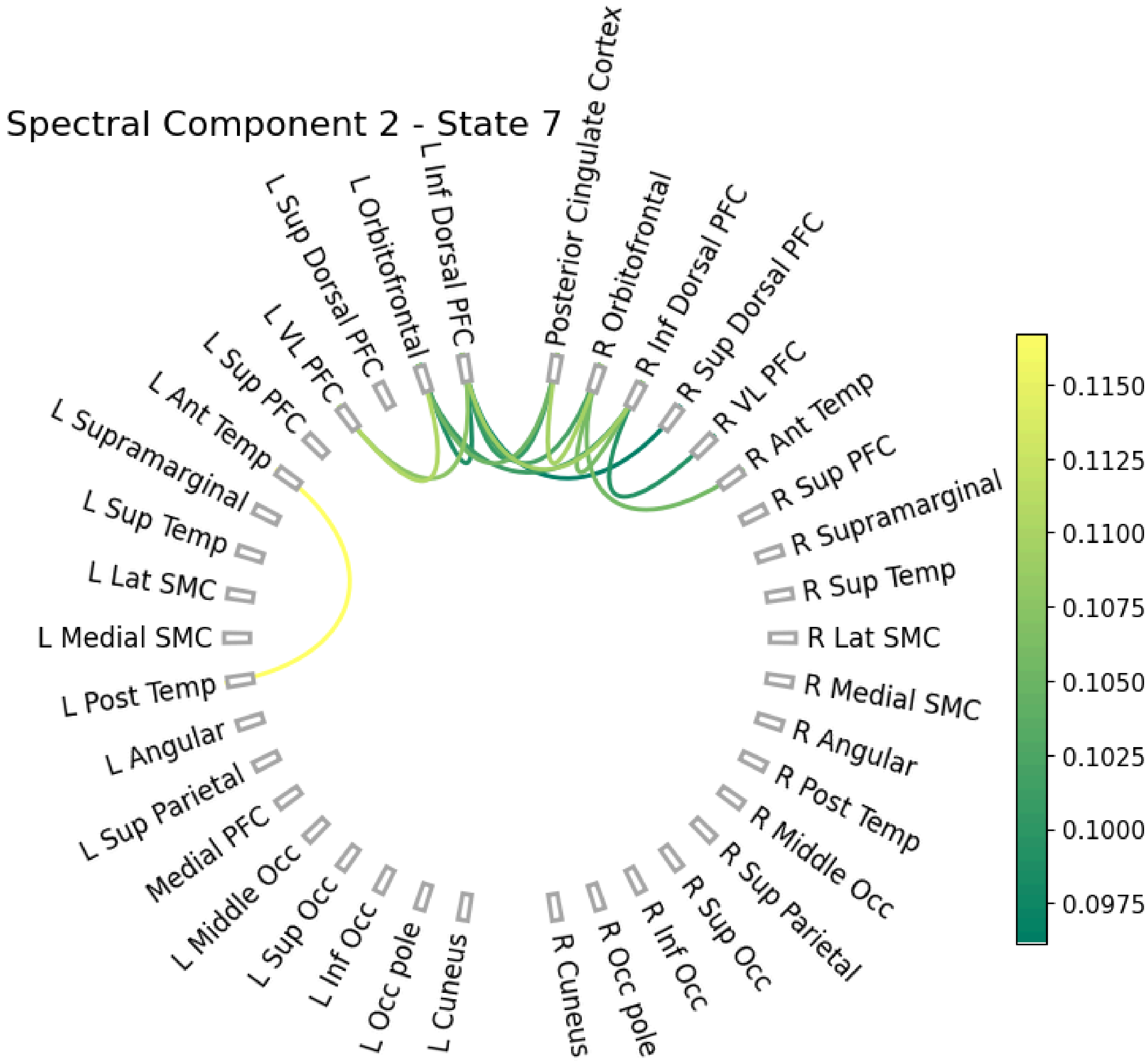
In [234…

```
connectivity_6states_SC2_S6 = connectivity_6states_SC2[5]

sc=1
title = 'Spectral Component 2 - State 6
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



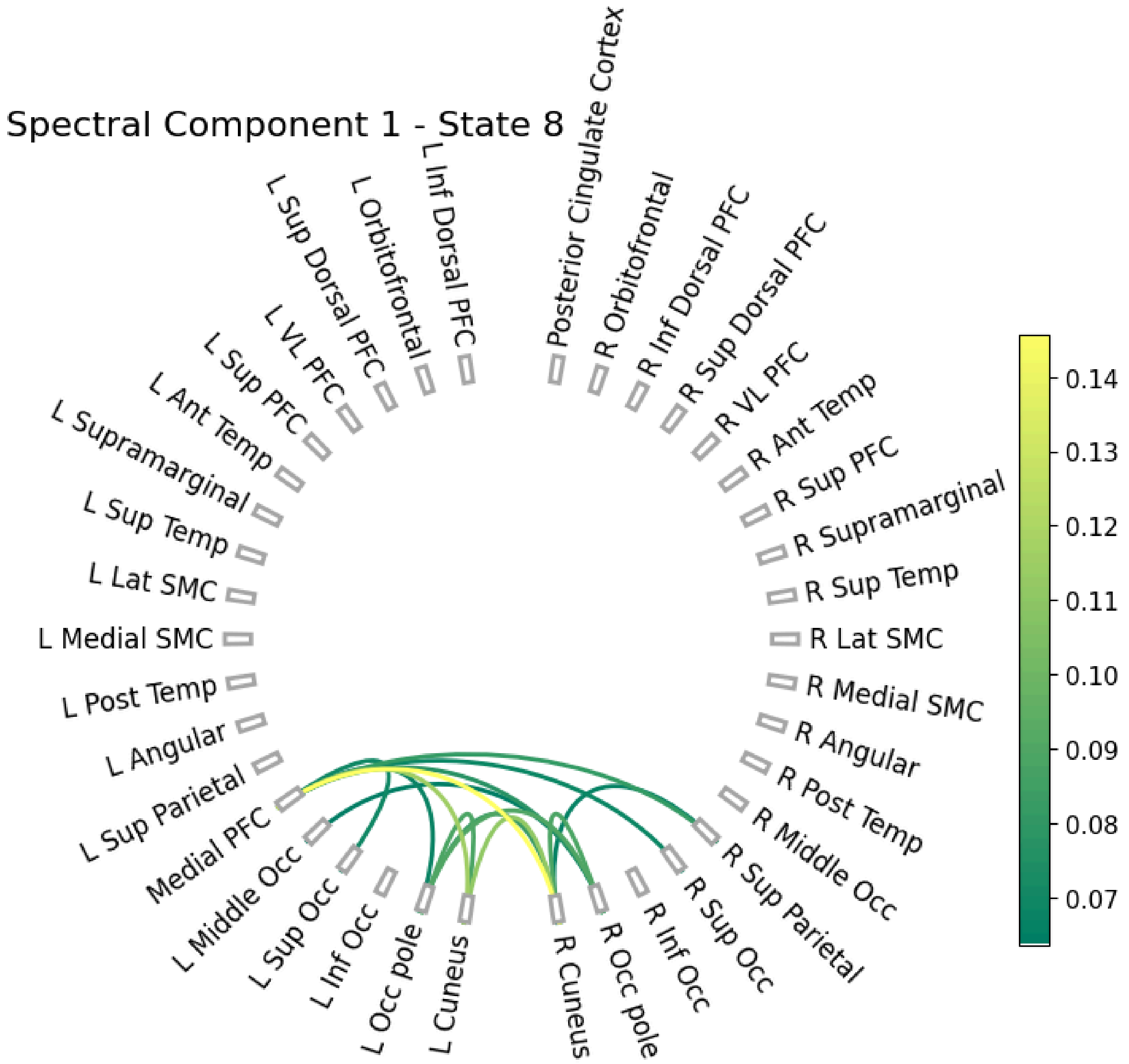
In [235…

```python
connectivity_6states_SC2_S7 = connectivity_6states_SC2[6]

sc=1
title = 'Spectral Component 2 - State 7
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



In [219…

```
connectivity_6states_SC2_S8 = connectivity_6states_SC2[7]

sc=1
title = 'Spectral Component 2 - State 8
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



Data-driven thresholding: Gaussian Mixture Model (GMM)

In [244…

```
mean_c = mean_c[:][:,np.array([True, True, True, True, False, True, True, Tı
print(np.shape(mean_c))
```

```
(4, 7, 38, 38)
```

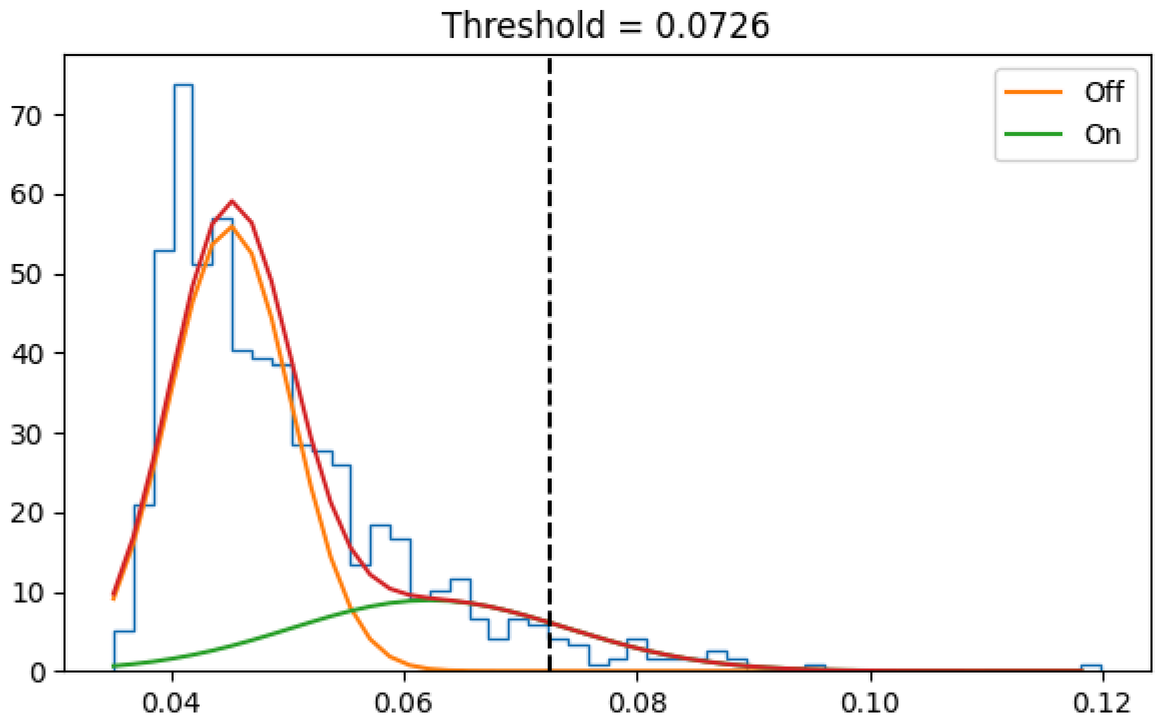
In [245…

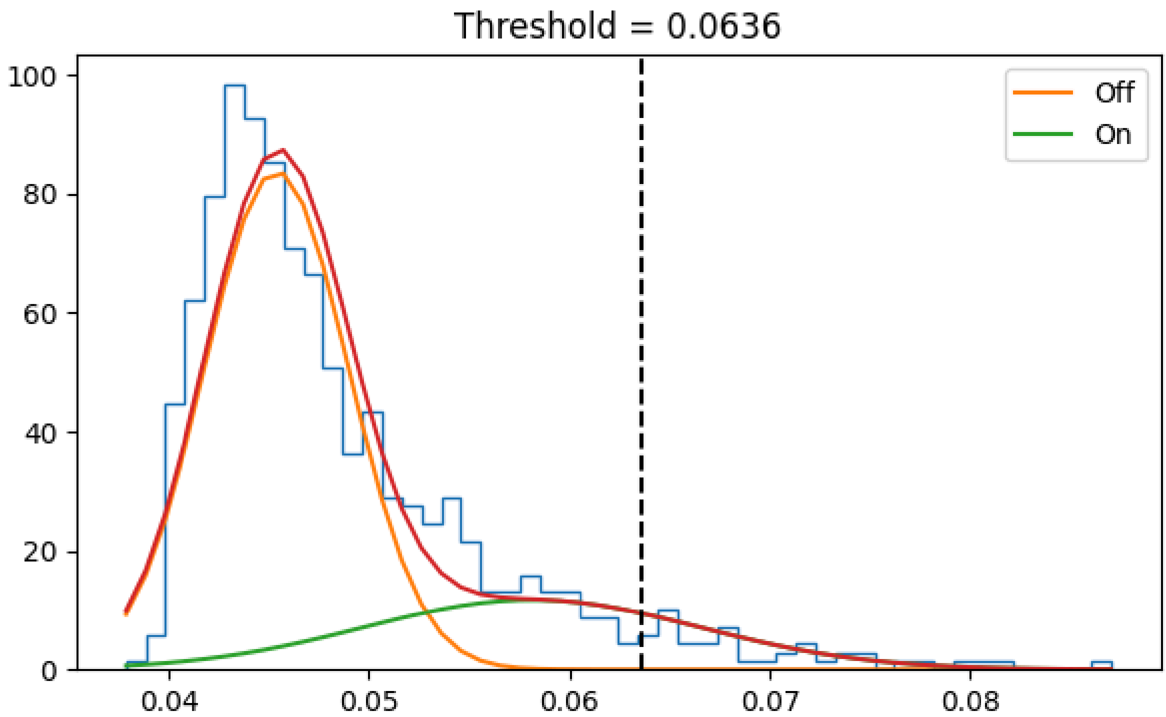
```
## This only needs to be ran once (it does the GMM data-driven thresholding

sc = 1

# Threshold each network using a GMM
thres_mean_c = connectivity.gmm_threshold(
    mean_c,
    p_value=0.05,
    keep_positive_only=True,
    #subtract_mean=True,
    show=True,
)
print(thres_mean_c.shape)

os.makedirs(model_name + "/data/Images" + "/Basic_Coherence_GMM", exist_ok=T
```

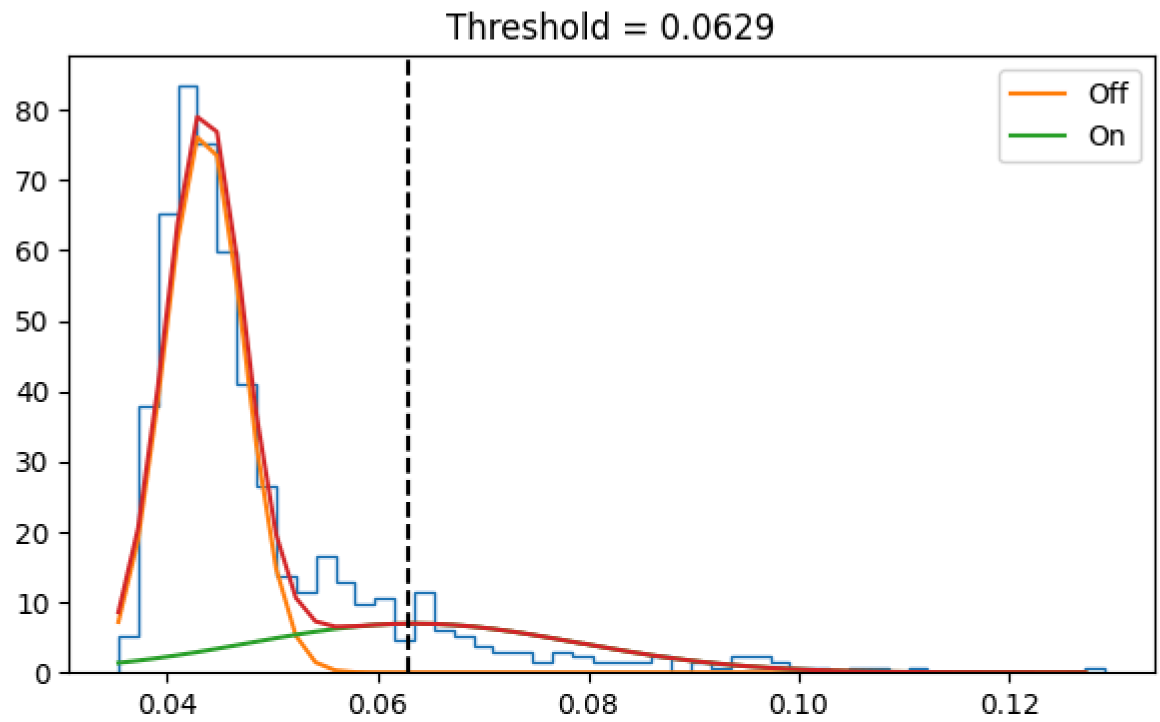
```
# Plot
connectivity.save(
    thres_mean_c,
    parcellation_file="/home/olivierb/38_parcels.nii",
    component=sc,
    filename=model_name + "/data/Images/Basic_Coherence_GMM/coh_Spectral_Com
)
```

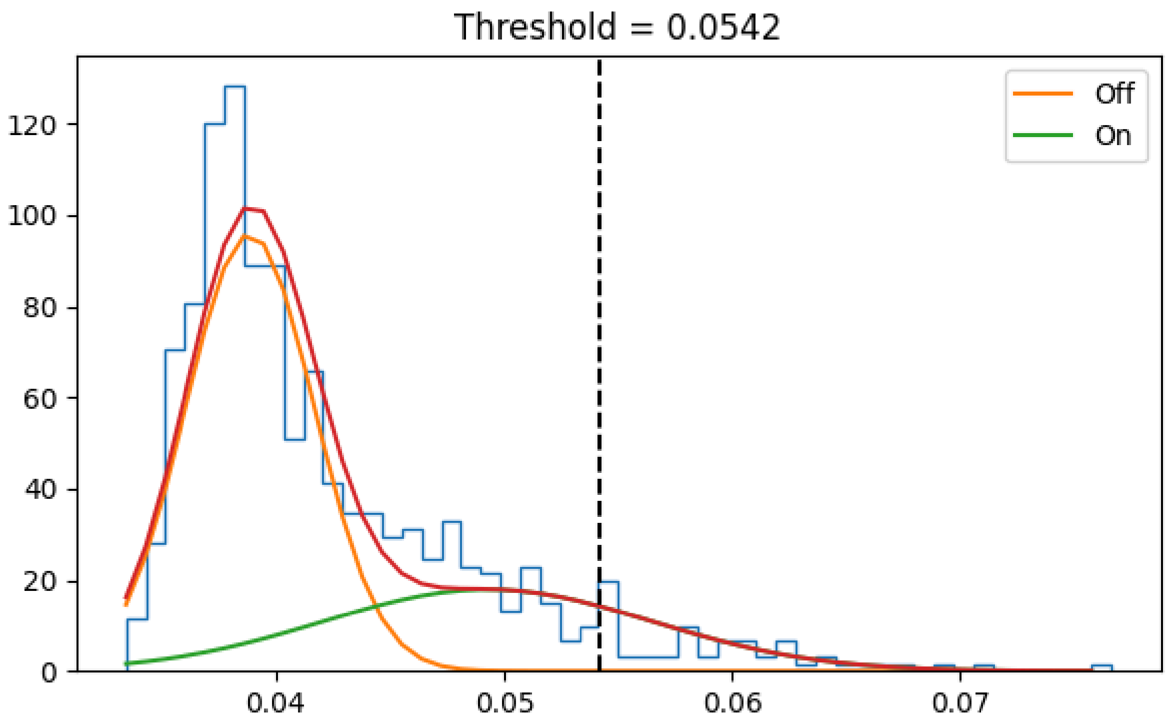
```
/home/olivierb/osl-dynamics/osl_dynamics/utils/plotting.py:72: RuntimeWarni
ng: More than 20 figures have been opened. Figures created through the pypl
ot interface (`matplotlib.pyplot.figure`) are retained until explicitly clo
sed and may consume too much memory. (To control this warning, see the rcPa
ram `figure.max_open_warning`). Consider using `matplotlib.pyplot.close()`.
  fig, ax = plt.subplots(*args, **kwargs)
(4, 7, 38, 38)
```

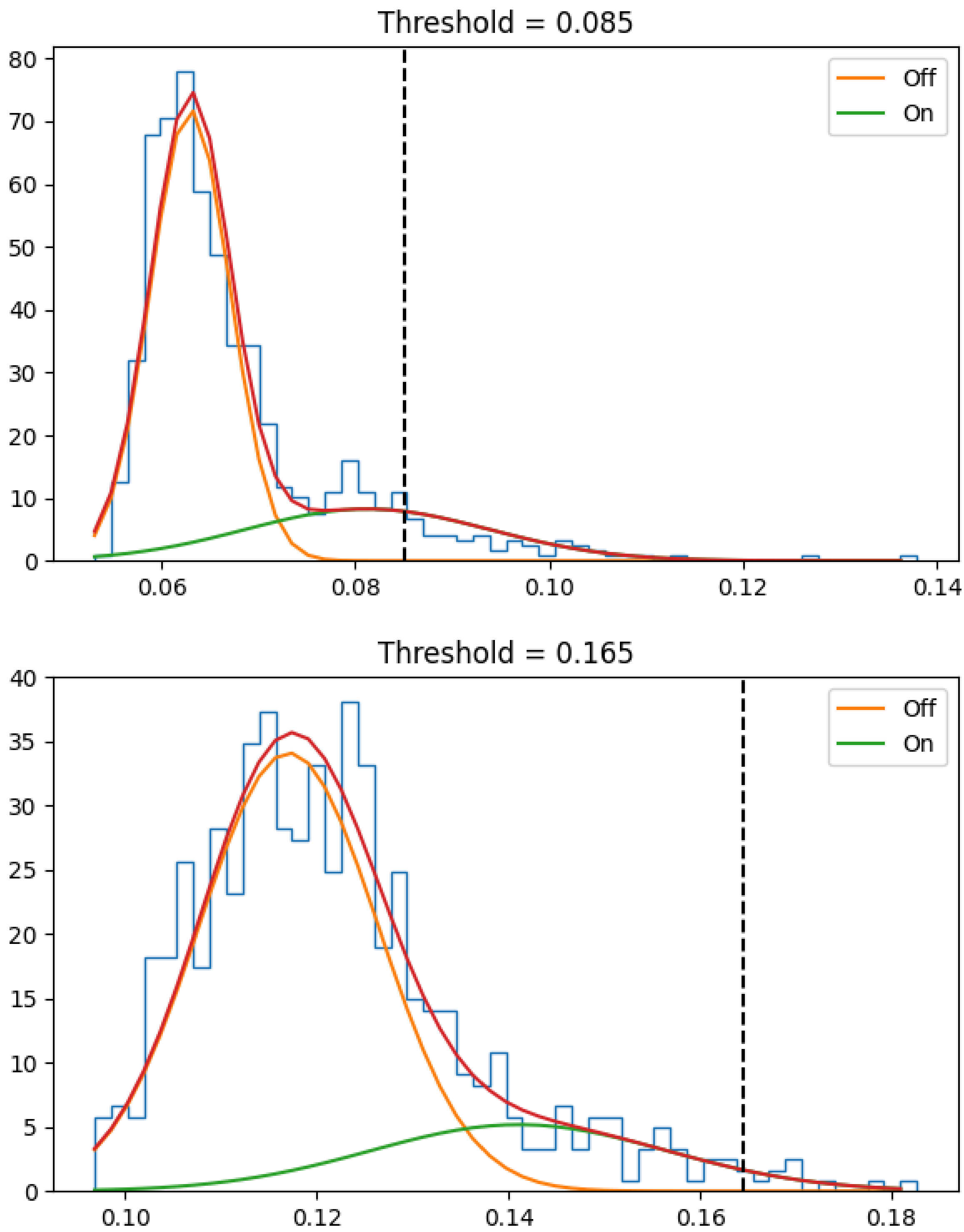
```
Saving images: 100%|██████████| 7/7 [00:08<00:00,  1.25s/it]
```

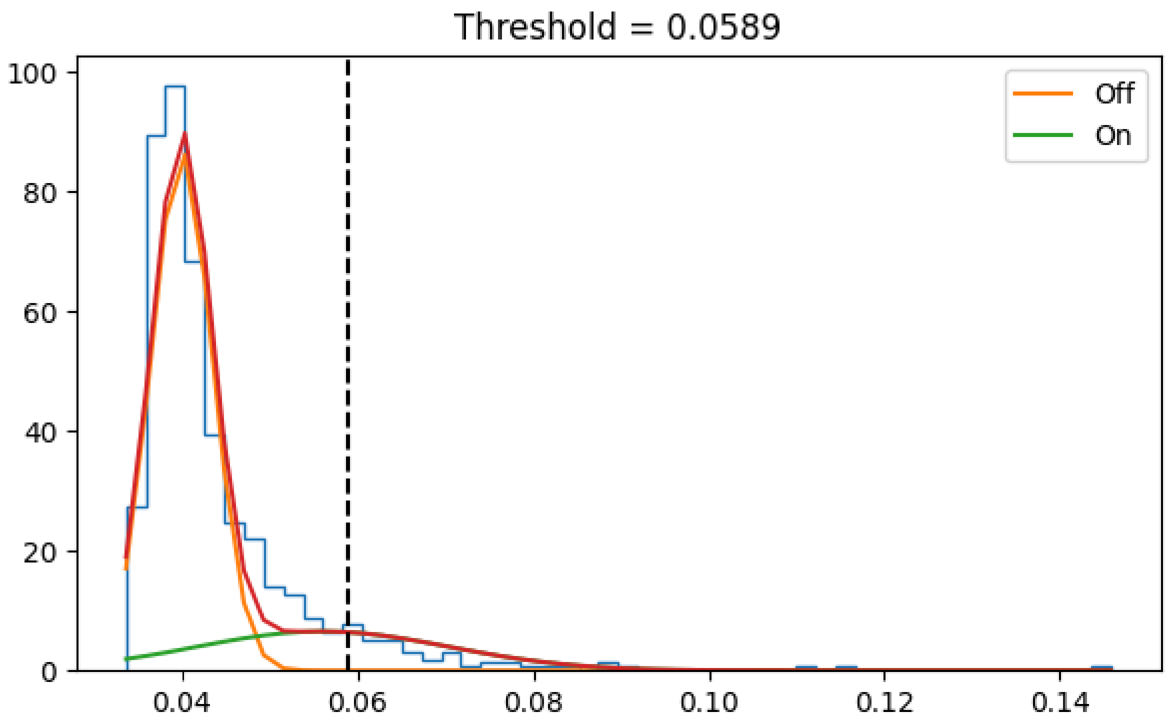


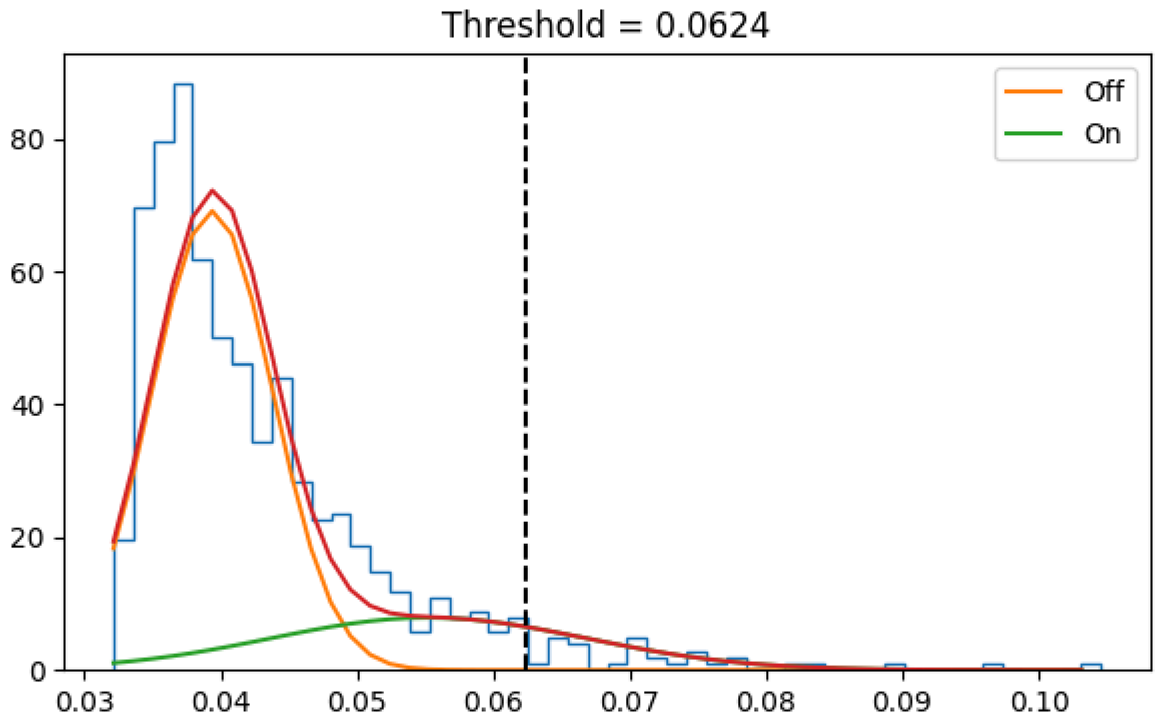


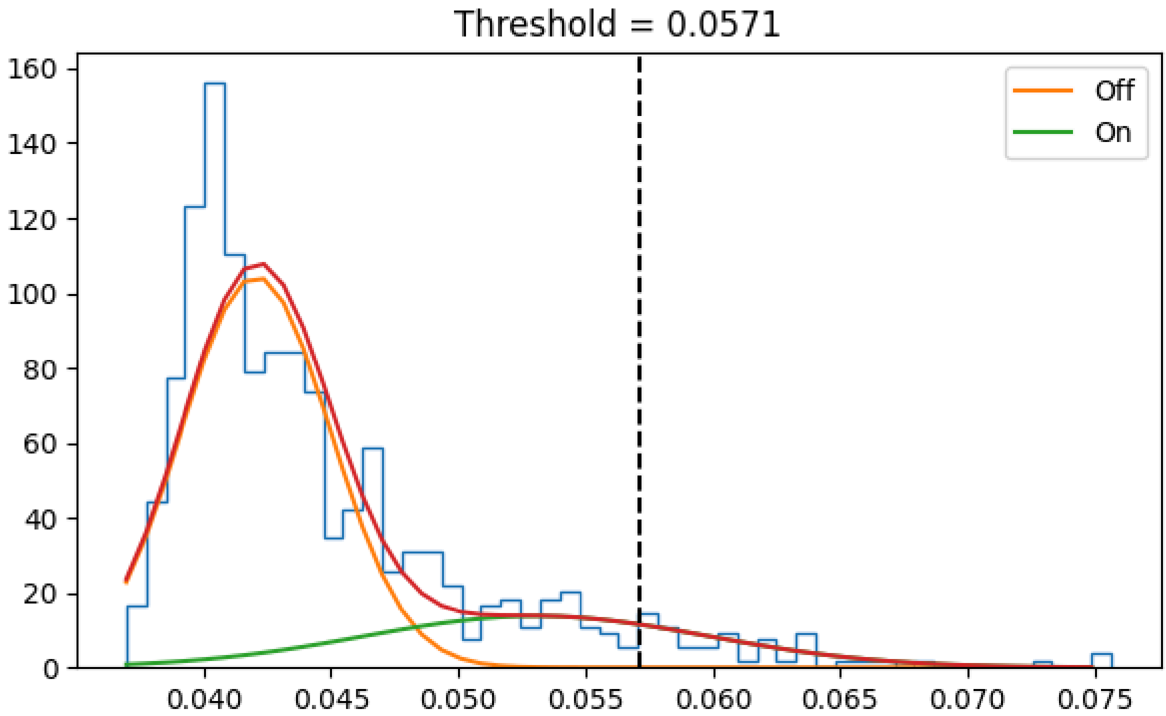

Threshold = 0.0629
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.06
0.08
0.10
0.12

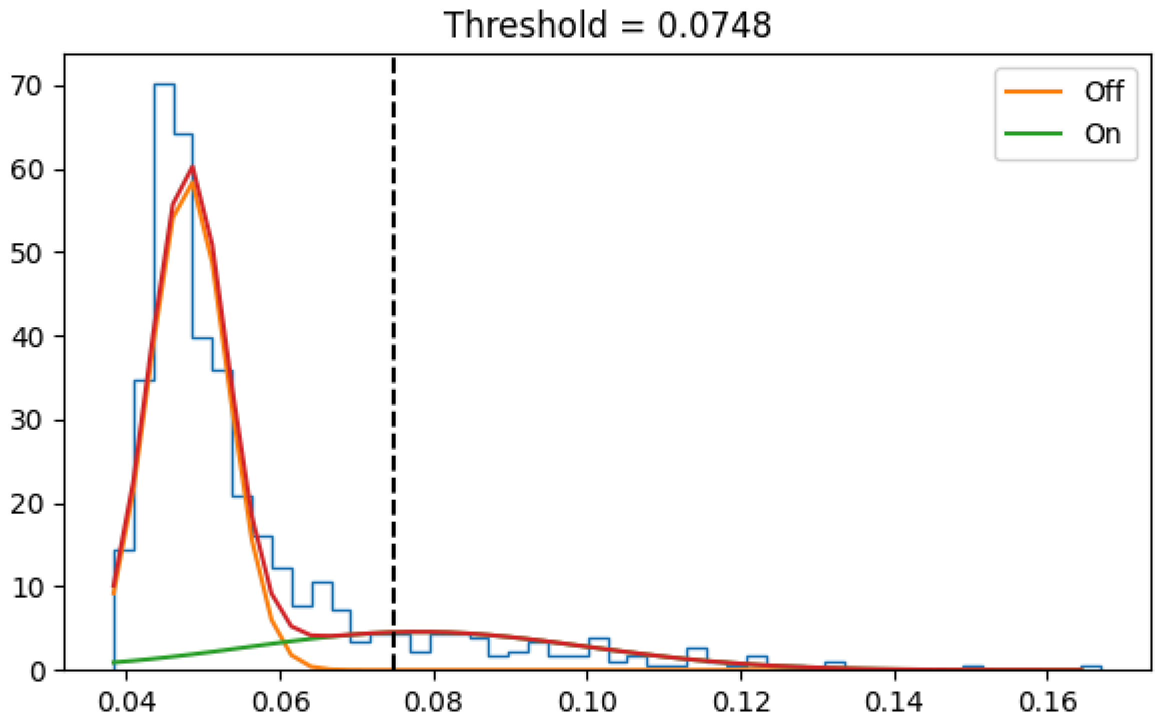

Threshold = 0.0542
Off
On
0
20
40
60
80
100
120
0.04
0.05
0.06
0.07

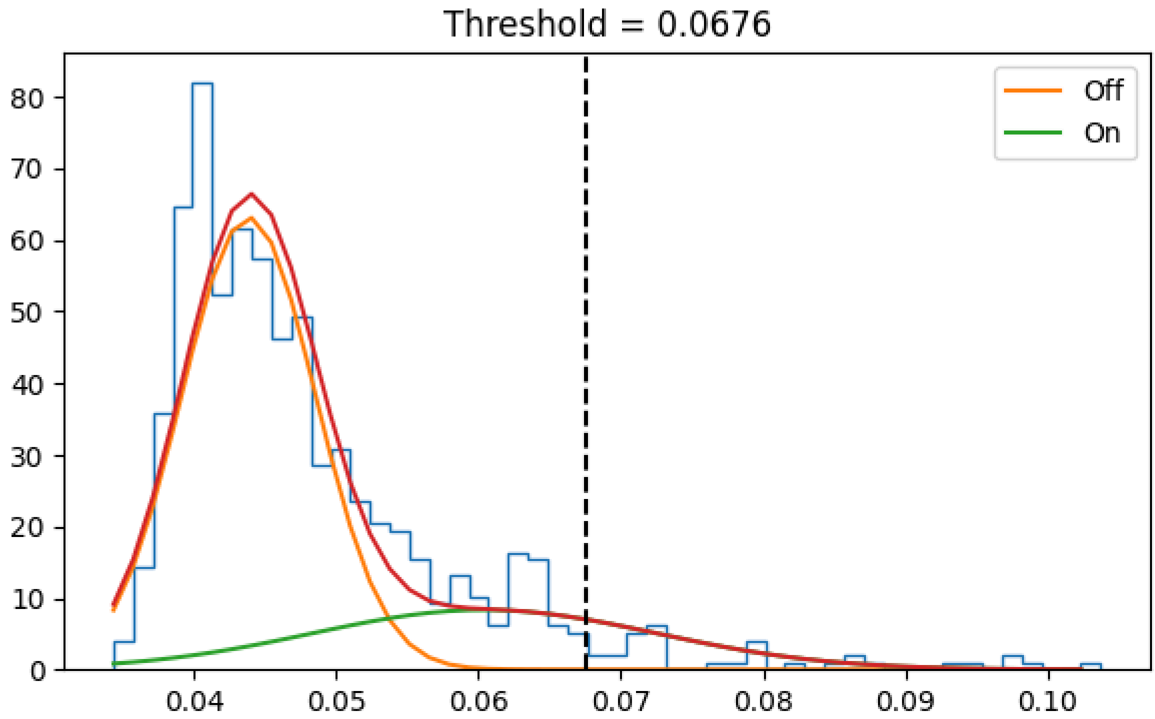

Threshold = 0.085
Off
On
0
10
20
30
40
50
60
70
80
0.06
0.08
0.10
0.12
0.14
Threshold = 0.165
Off
On
0
5
10
15
20
25
30
35
40
0.10
0.12
0.14
0.16
0.18

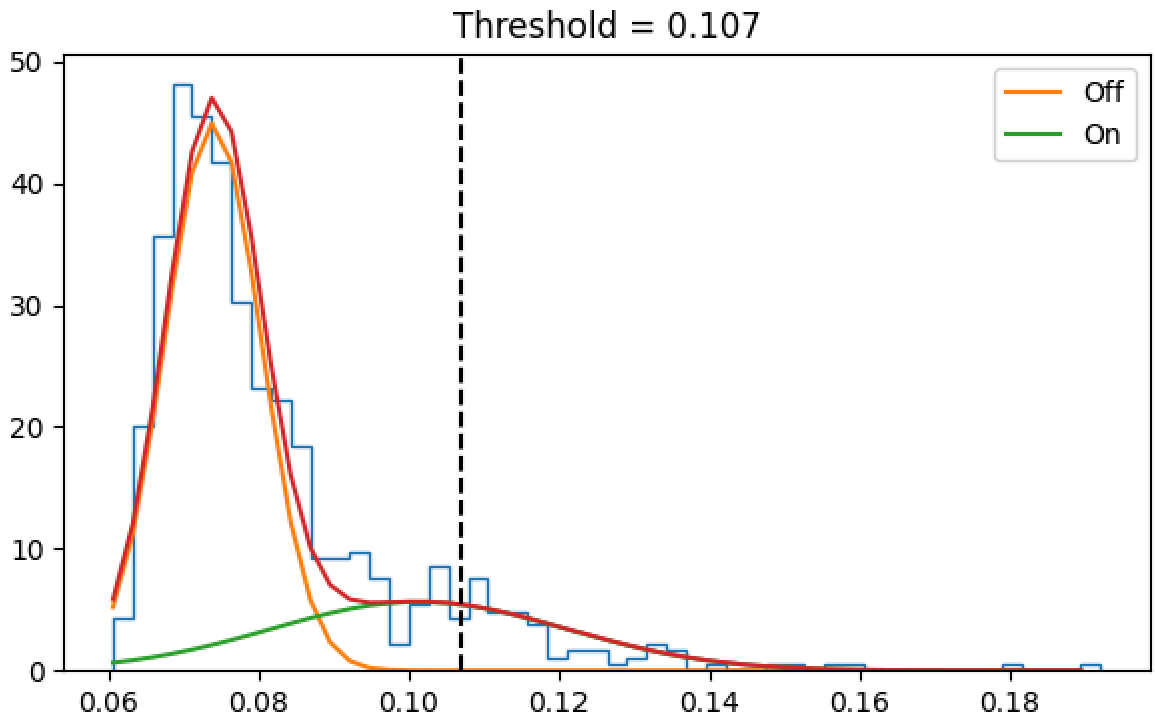

Threshold = 0.0589
Off
On
100
80
60
40
20
0
0.04
0.06
0.08
0.10
0.12
0.14

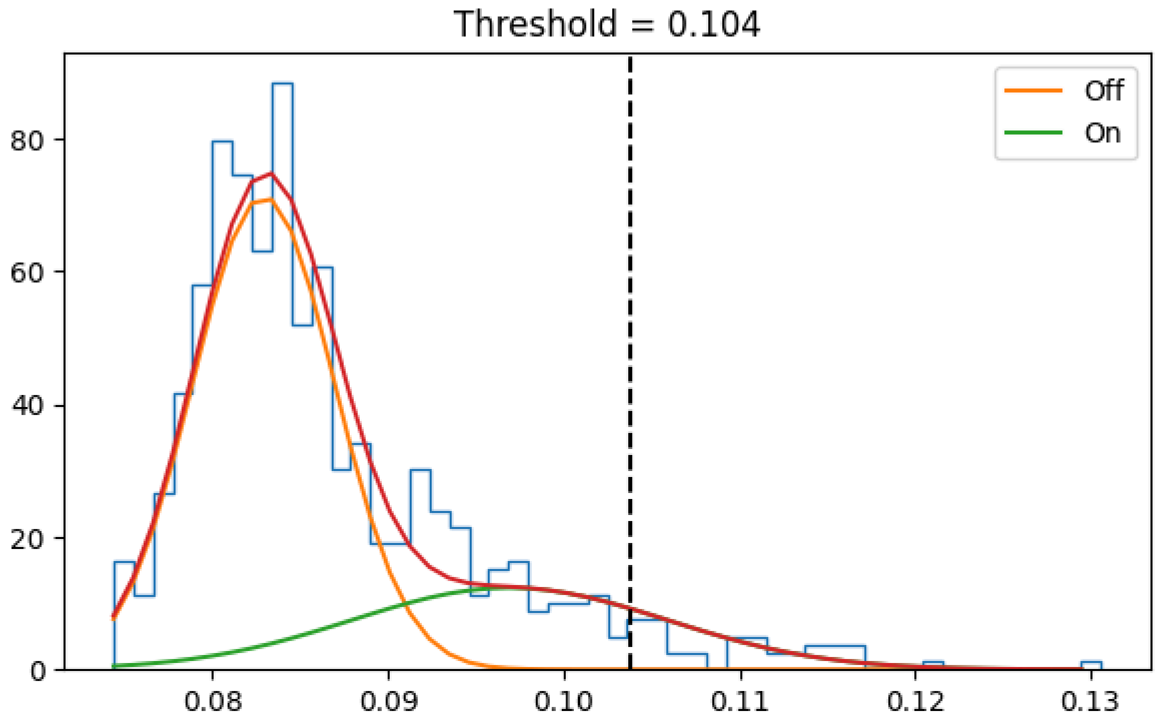

Threshold = 0.0624
Off
On
80
60
40
20
0
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10

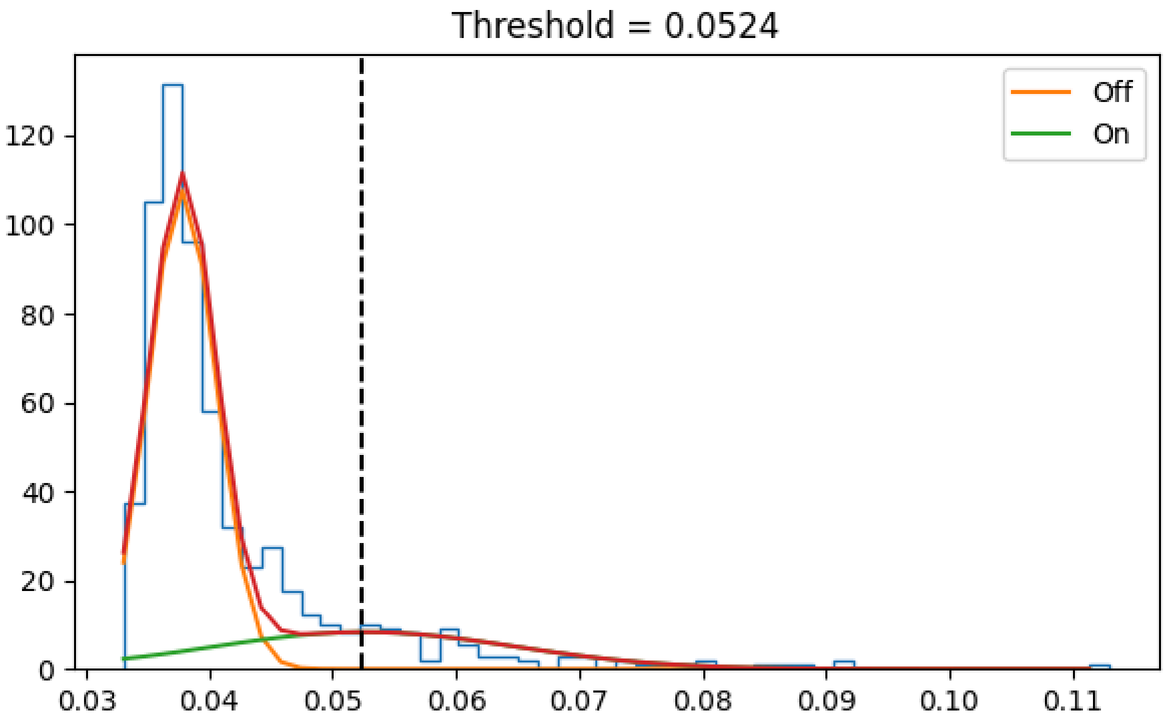

Threshold = 0.0571
Off
On
160
140
120
100
80
60
40
20
0
0.040
0.045
0.050
0.055
0.060
0.065
0.070
0.075

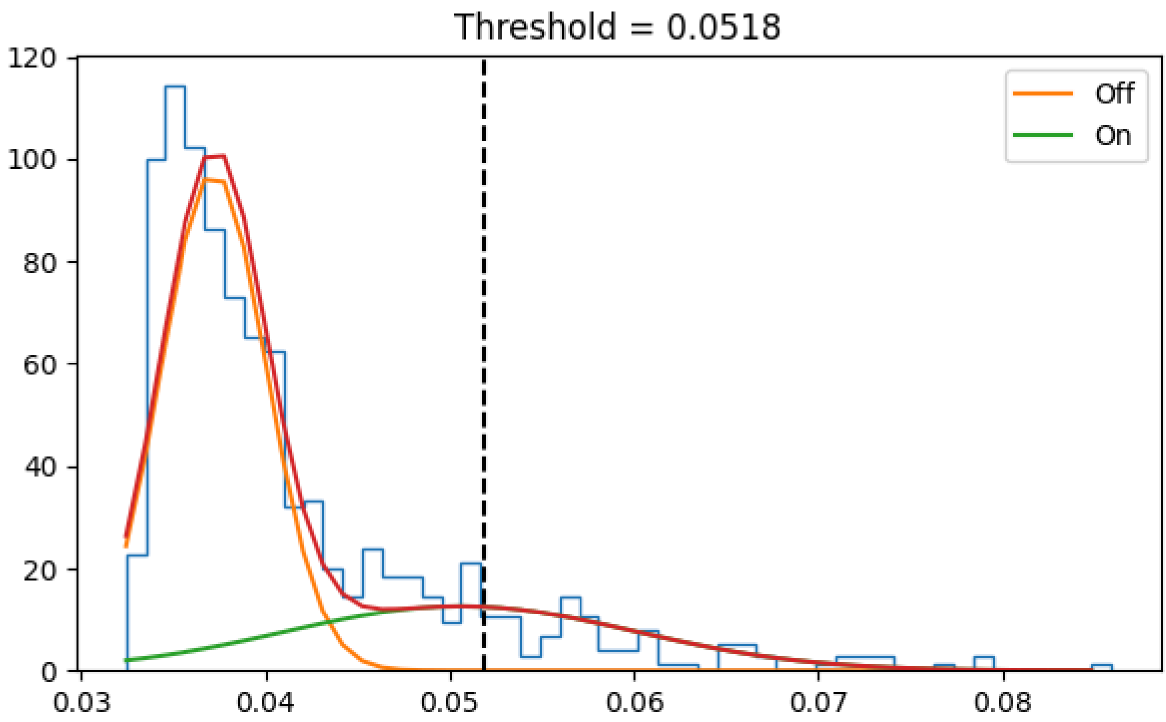

Threshold = 0.0748
Off
On
70
60
50
40
30
20
10
0
0.04
0.06
0.08
0.10
0.12
0.14
0.16

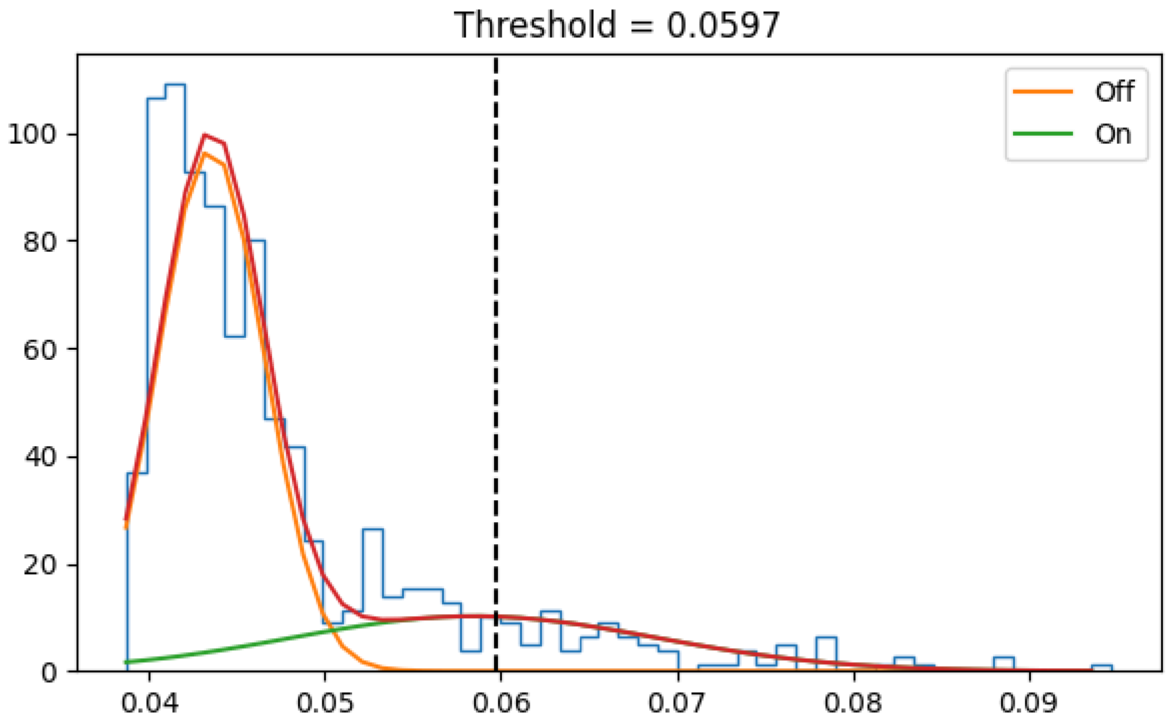

Threshold = 0.0676
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.05
0.06
0.07
0.08
0.09
0.10

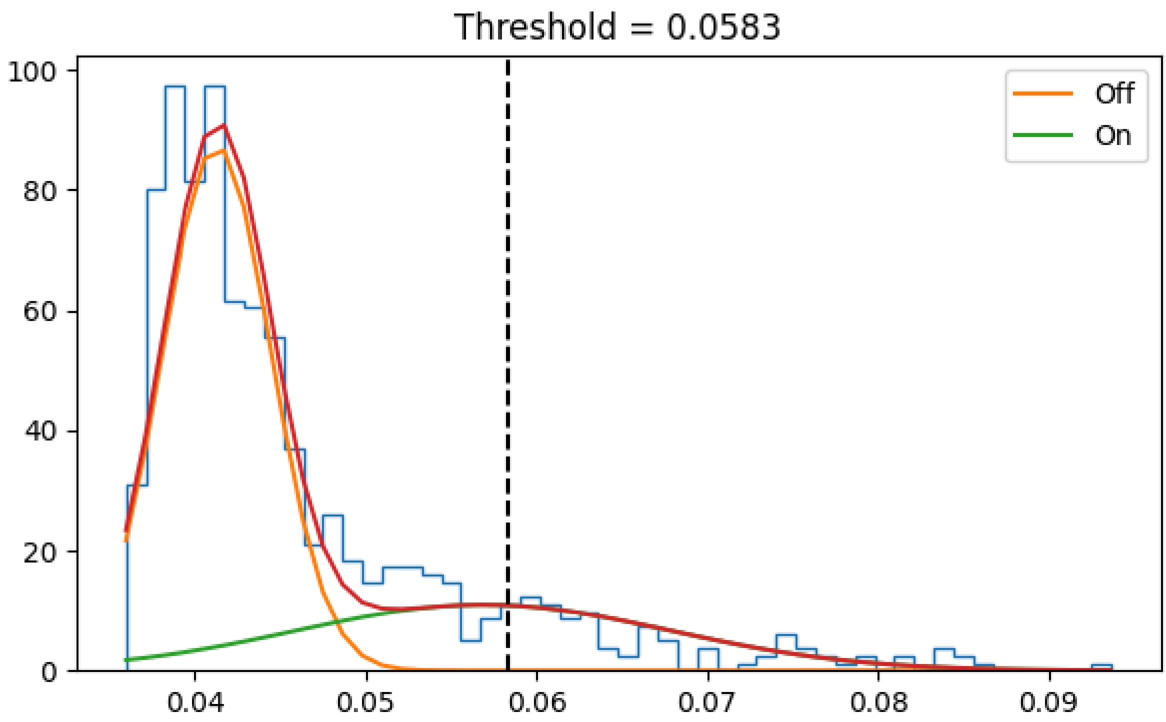

Threshold = 0.107
Off
On
0
10
20
30
40
50
0.06
0.08
0.10
0.12
0.14
0.16
0.18

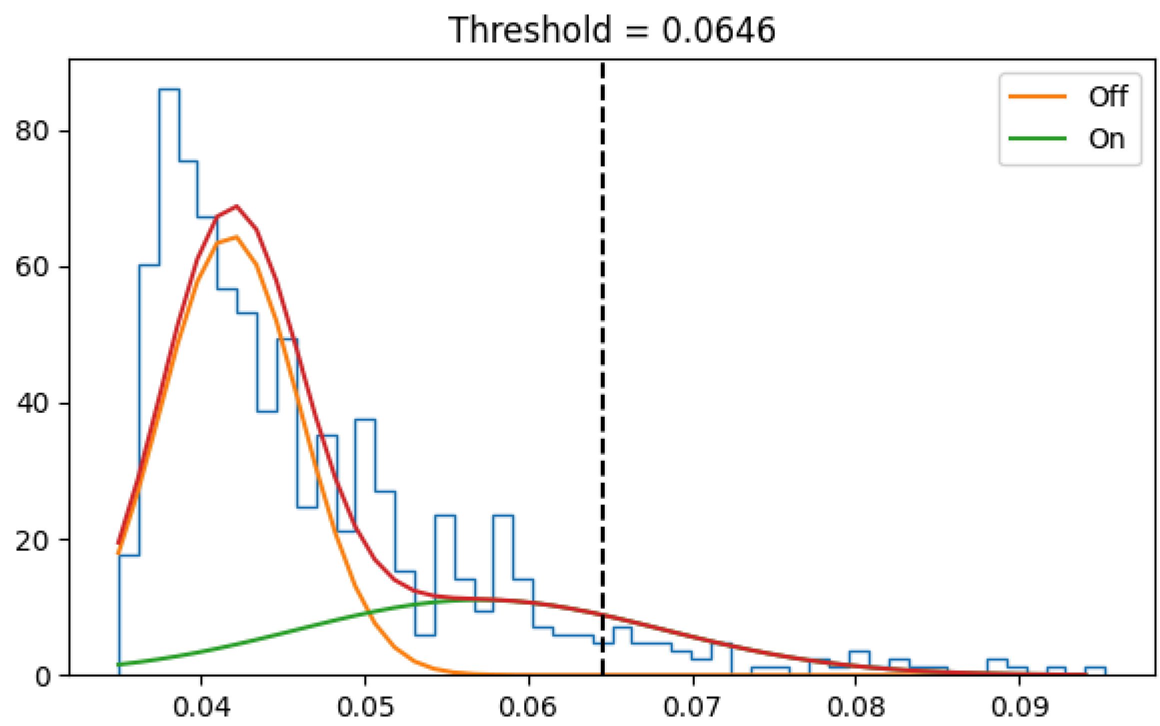

Threshold = 0.104
Off
On
0
20
40
60
80
0.08
0.09
0.10
0.11
0.12
0.13

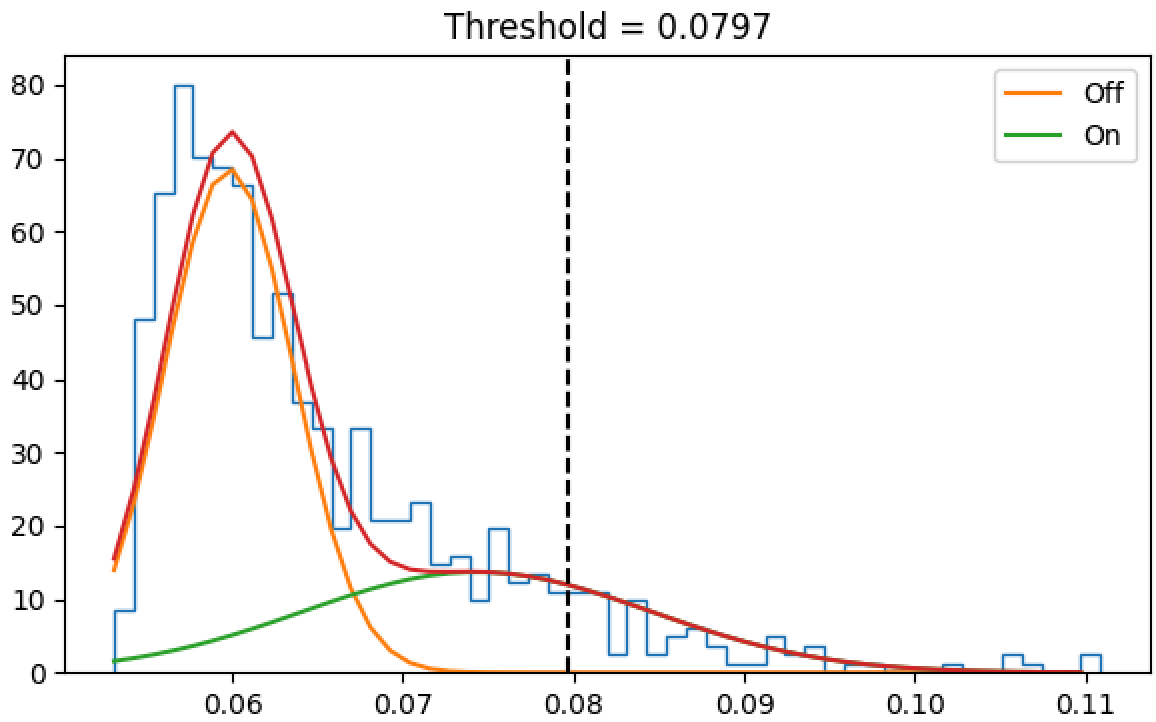

Threshold = 0.0524
Off
On
0
20
40
60
80
100
120
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10
0.11

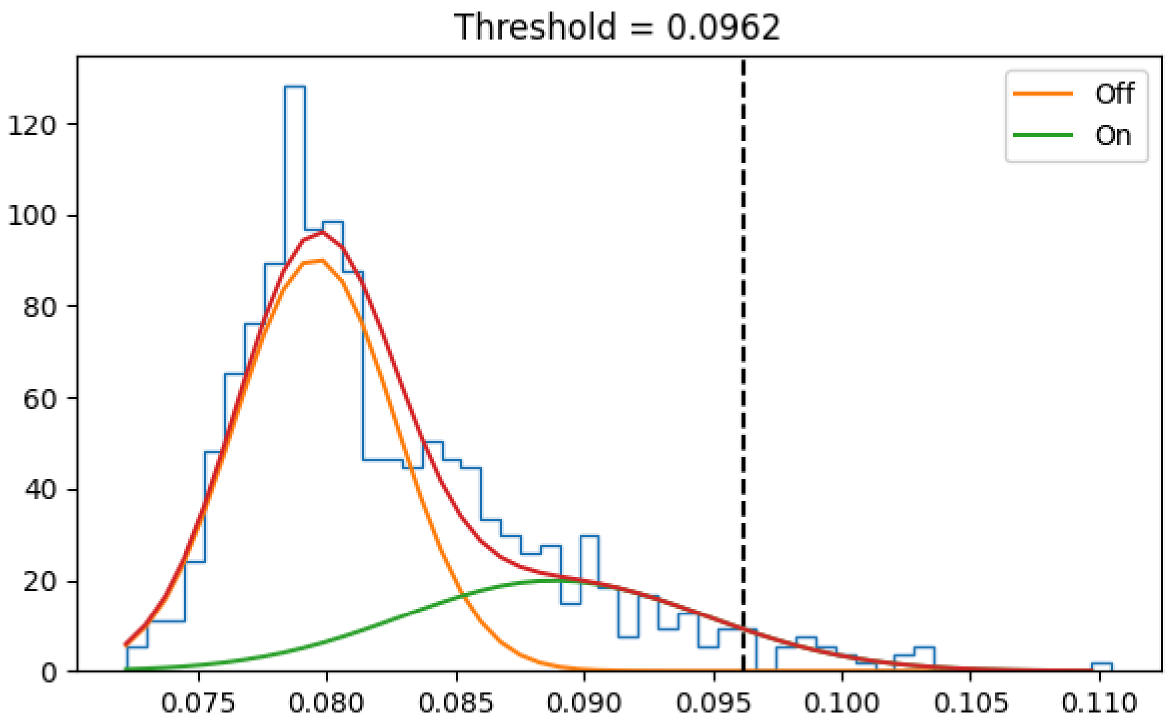

Threshold = 0.0518
Off
On
0
20
40
60
80
100
120
0.03
0.04
0.05
0.06
0.07
0.08

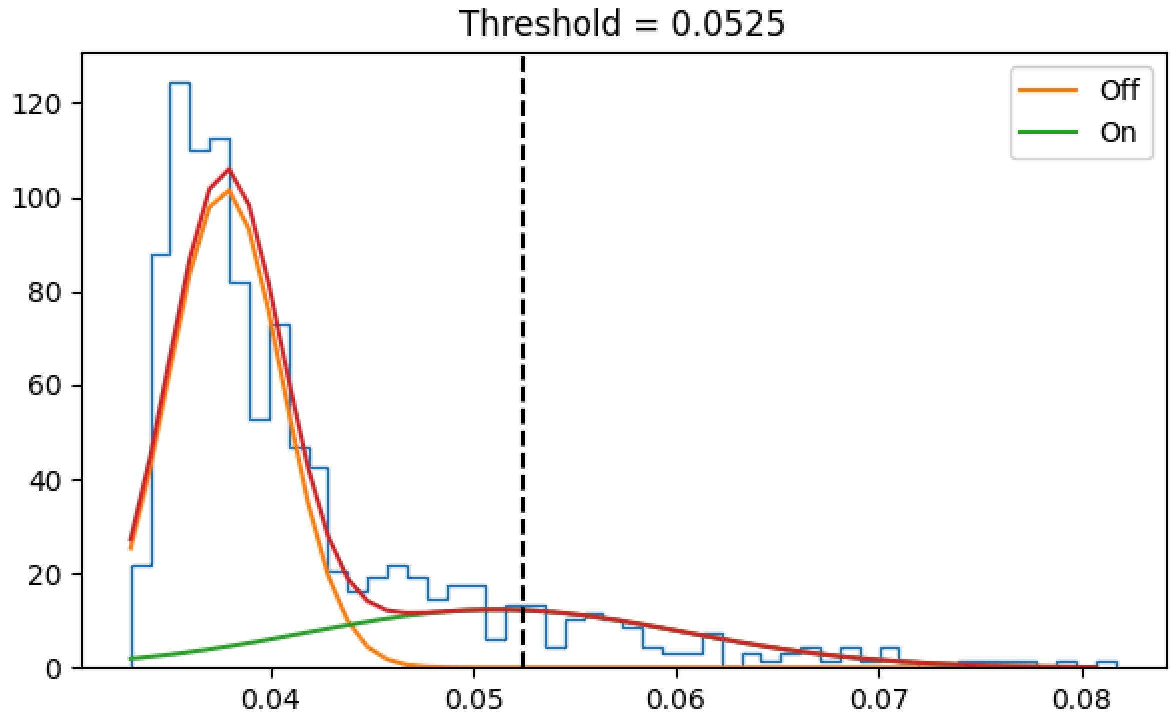

Threshold = 0.0597
Off
On
0
20
40
60
80
100
0.04
0.05
0.06
0.07
0.08
0.09

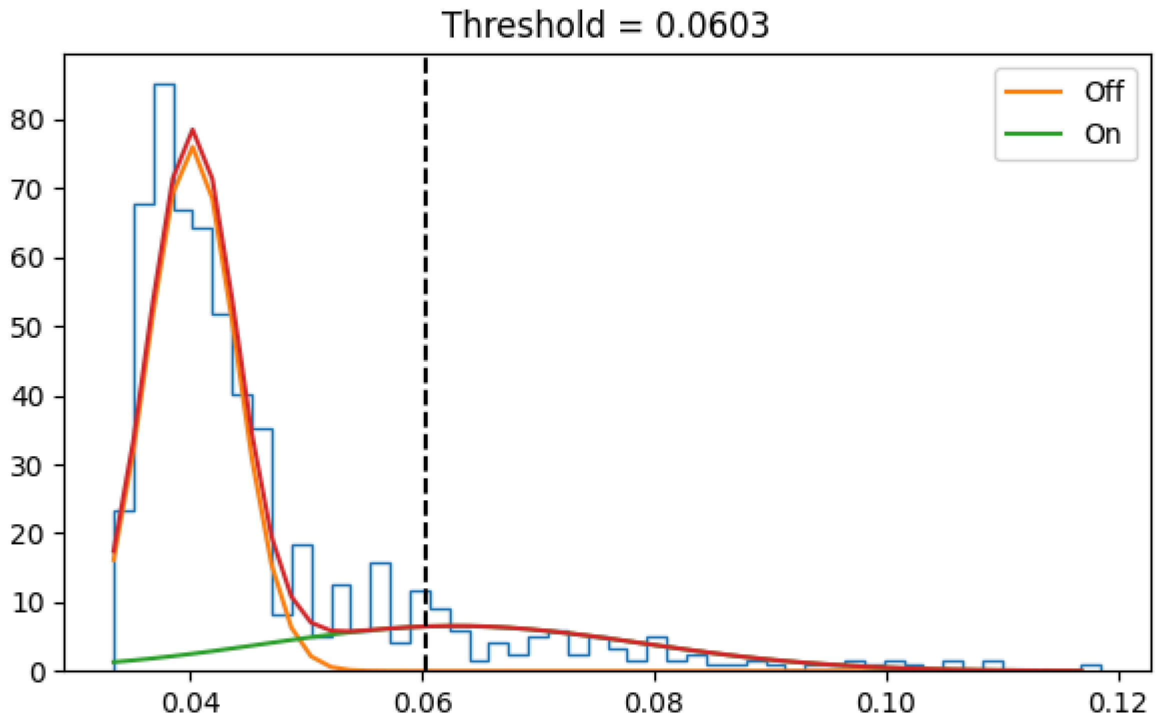

Threshold = 0.0583
Off
On
100
80
60
40
20
0
0.04
0.05
0.06
0.07
0.08
0.09

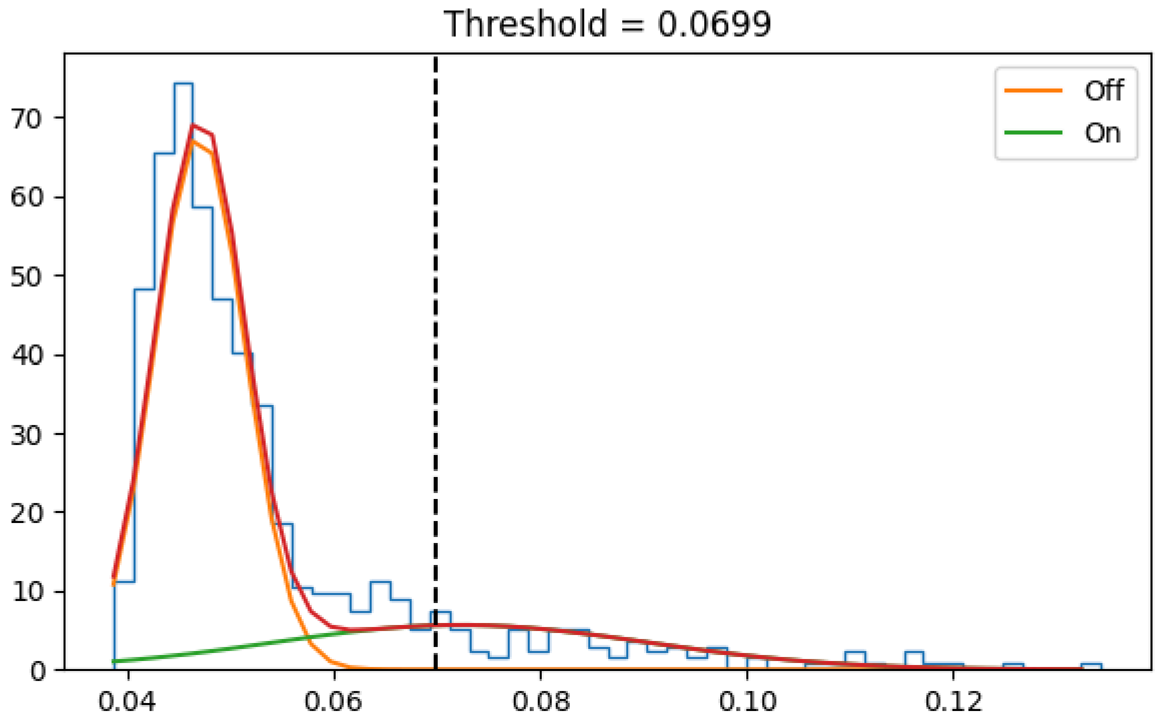

Threshold = 0.0646
Off
On
80
60
40
20
0
0.04
0.05
0.06
0.07
0.08
0.09

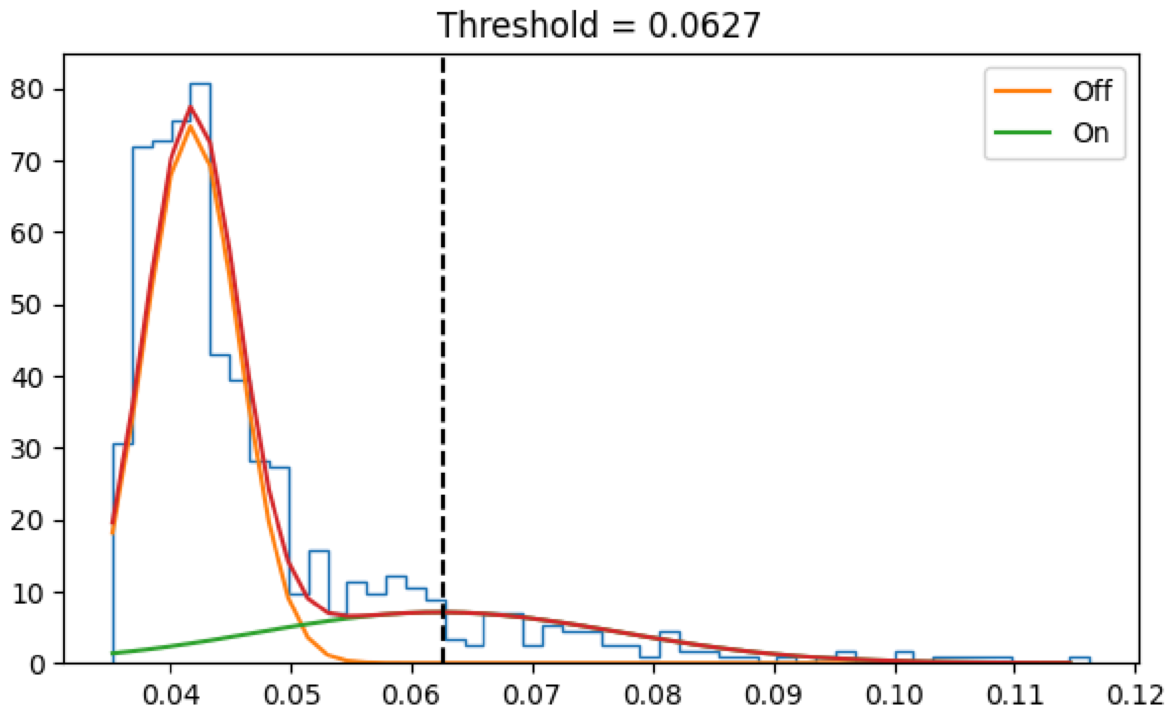

Threshold = 0.0797
Off
On
0
10
20
30
40
50
60
70
80
0.06
0.07
0.08
0.09
0.10
0.11

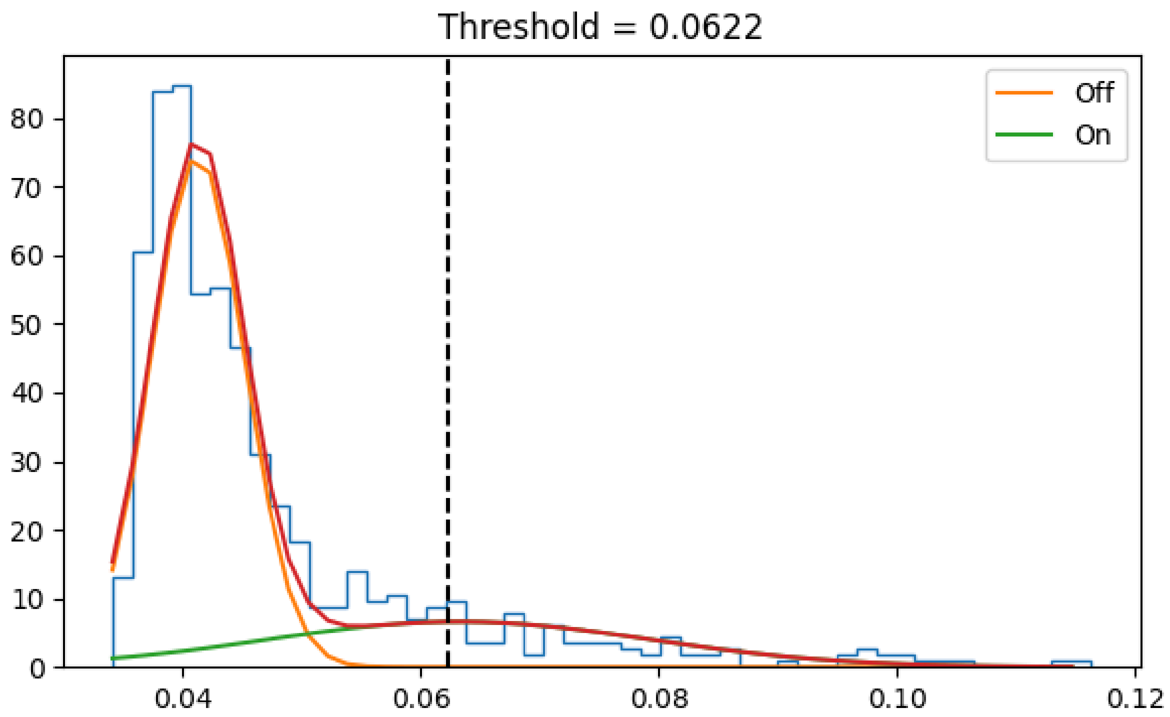

Threshold = 0.0962
Off
On
0
20
40
60
80
100
120
0.075
0.080
0.085
0.090
0.095
0.100
0.105
0.110

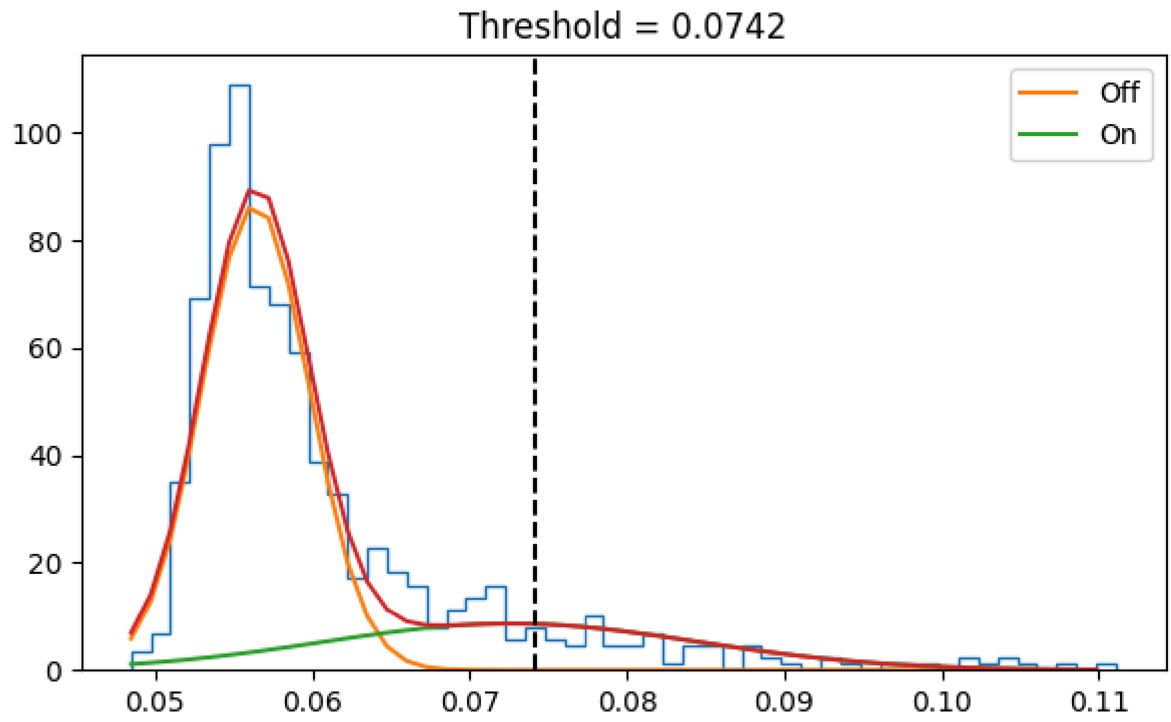

Threshold = 0.0525
Off
On
120
100
80
60
40
20
0
0.04
0.05
0.06
0.07
0.08

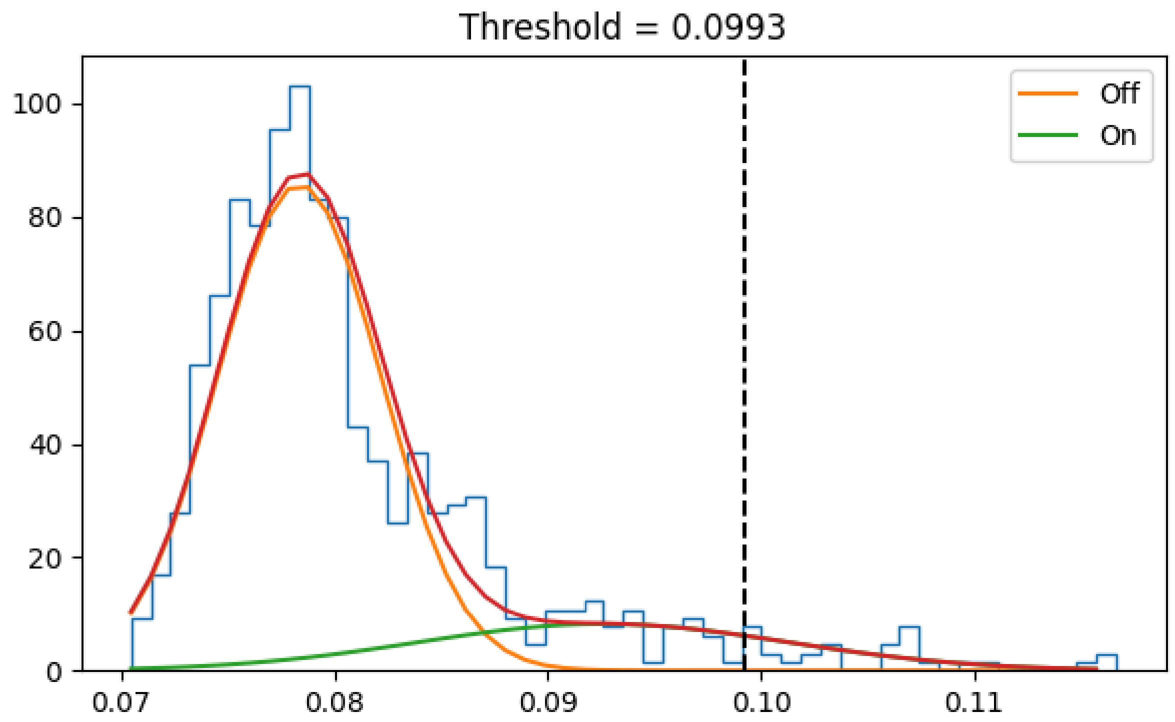

Threshold = 0.0603
Off
On
80
70
60
50
40
30
20
10
0
0.04
0.06
0.08
0.10
0.12

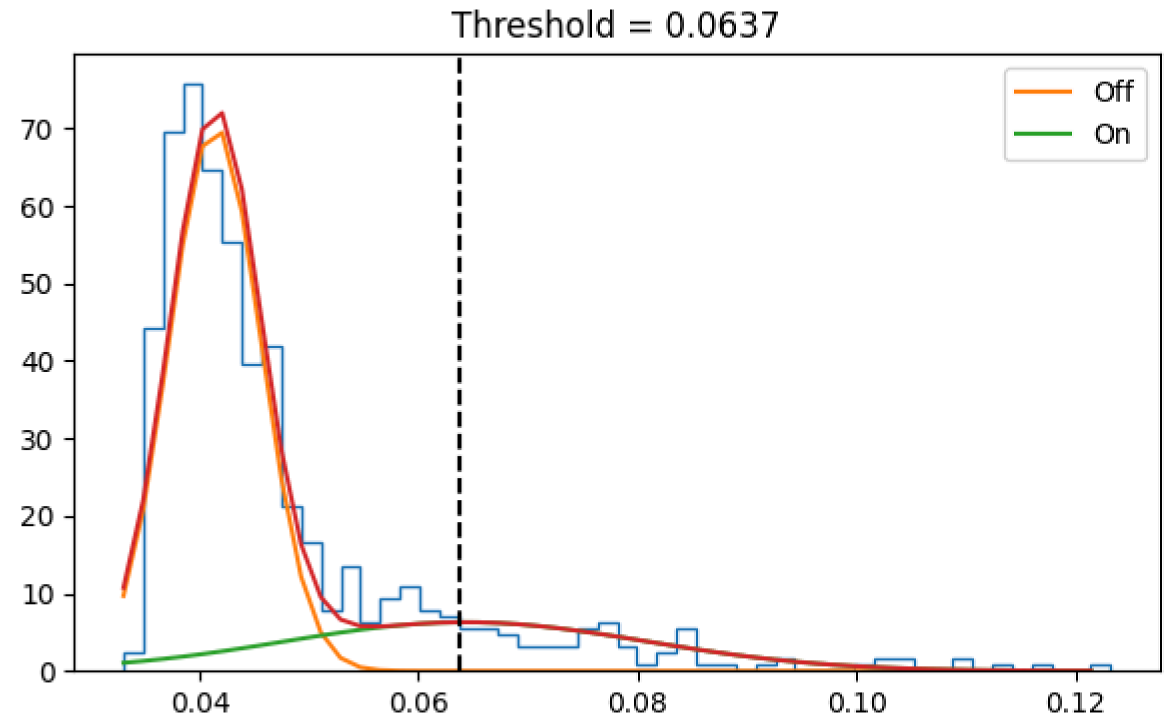

Threshold = 0.0699
Off
On
0
10
20
30
40
50
60
70
0.04
0.06
0.08
0.10
0.12


Threshold = 0.0627
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.05
0.06
0.07
0.08
0.09
0.10
0.11
0.12


Threshold = 0.0622
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.06
0.08
0.10
0.12


Threshold = 0.0742
Off
On
0
20
40
60
80
100
0.05
0.06
0.07
0.08
0.09
0.10
0.11

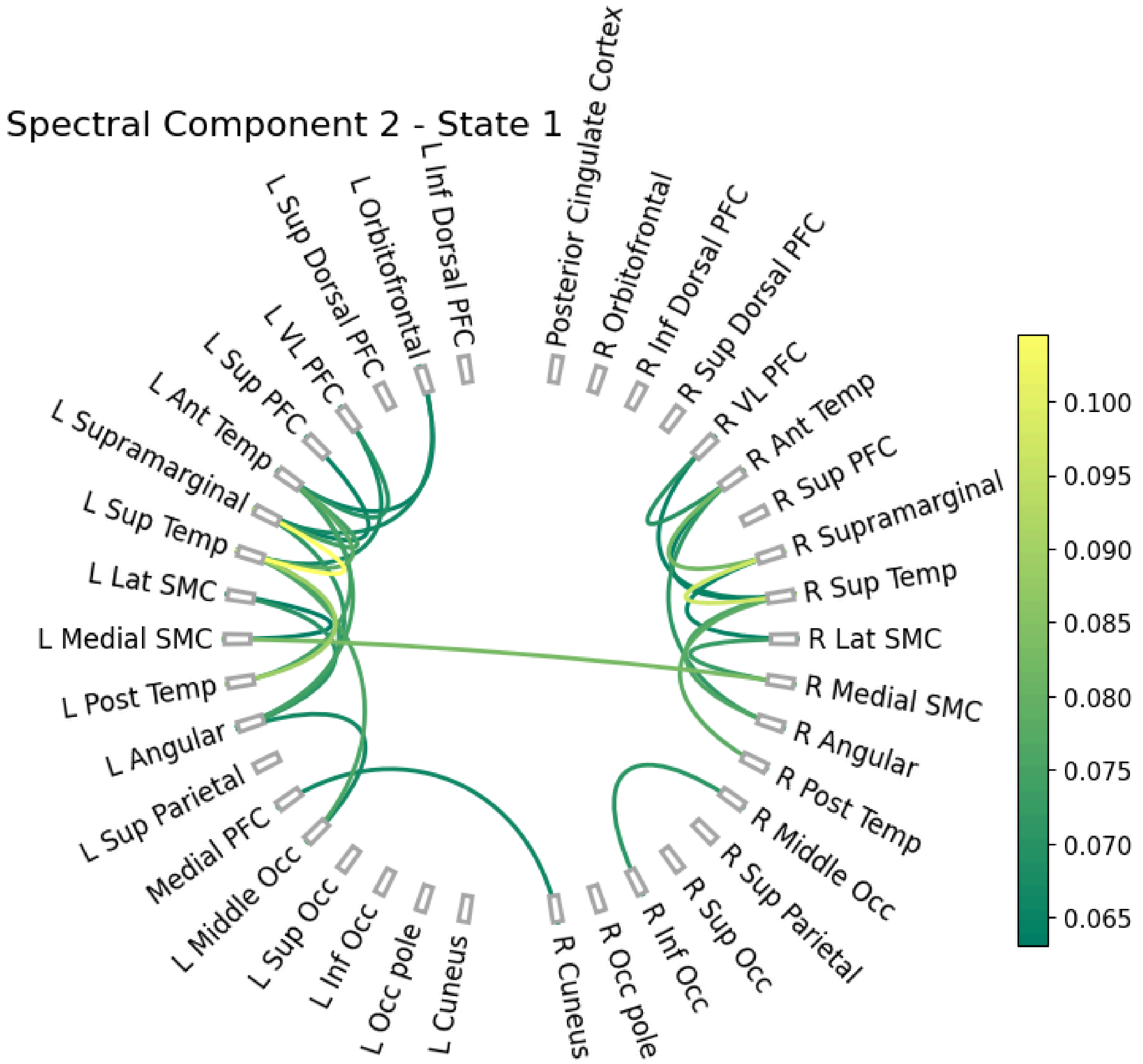




Spectral component 2

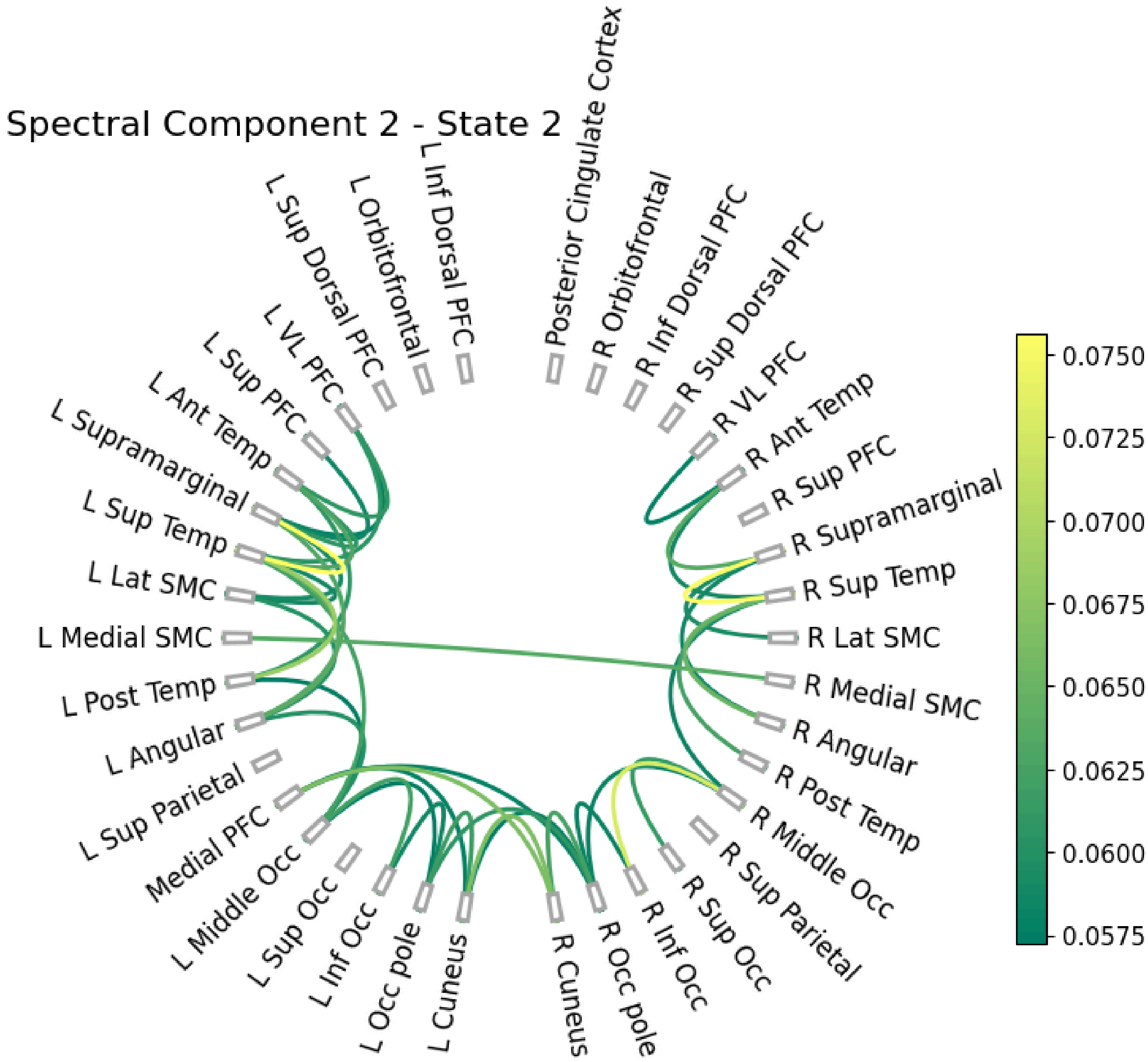
In [246…

```
connectivity_6states_SC2_S1 = thres_mean_c[1][0]  # comp 2 state 1

sc=1
title = 'Spectral Component 2 - State 1
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



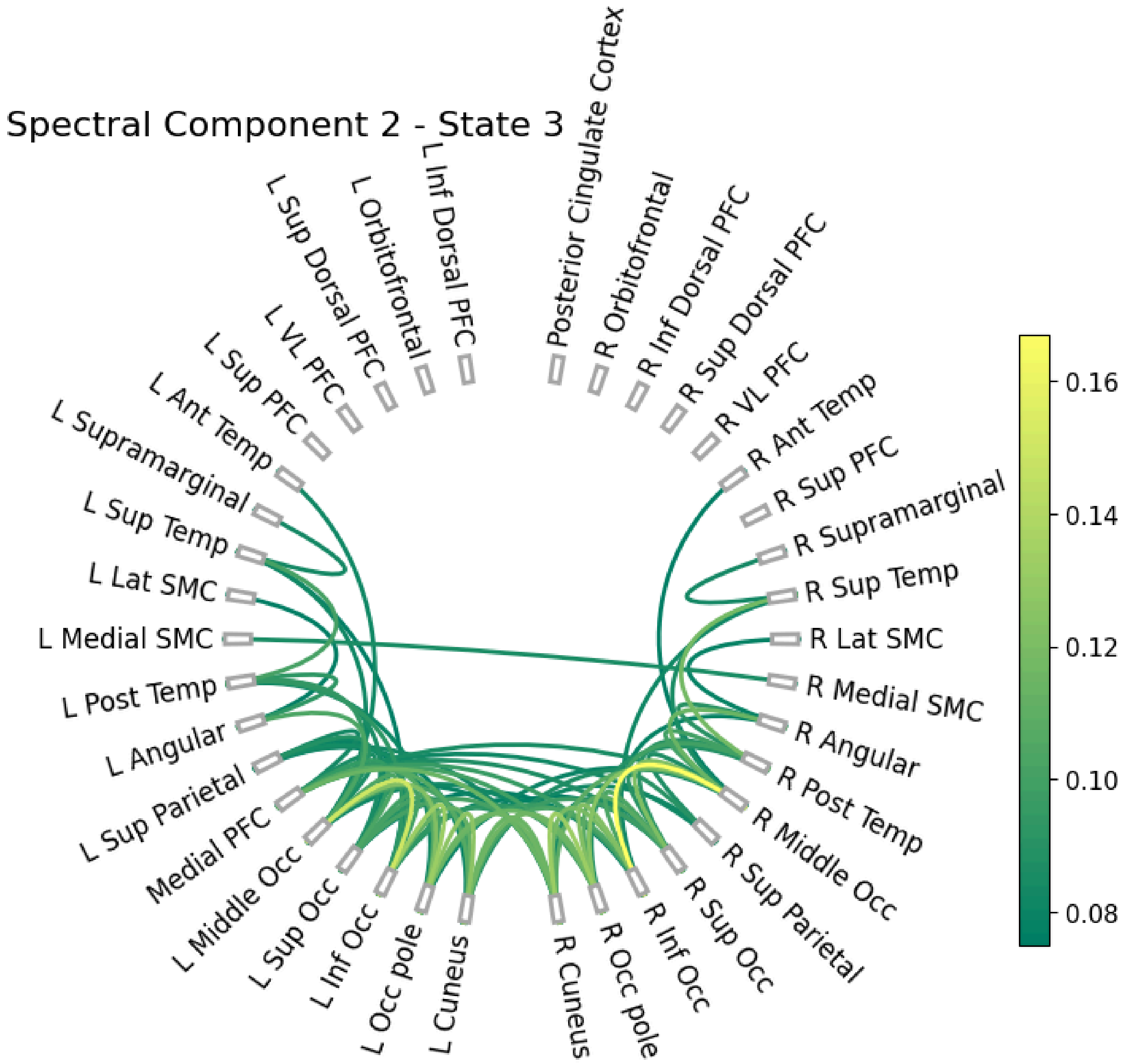
In [247…

```
connectivity_6states_SC2_S2 = thres_mean_c[1][1]   # comp 2 state 2

sc=1
title = 'Spectral Component 2 - State 2
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



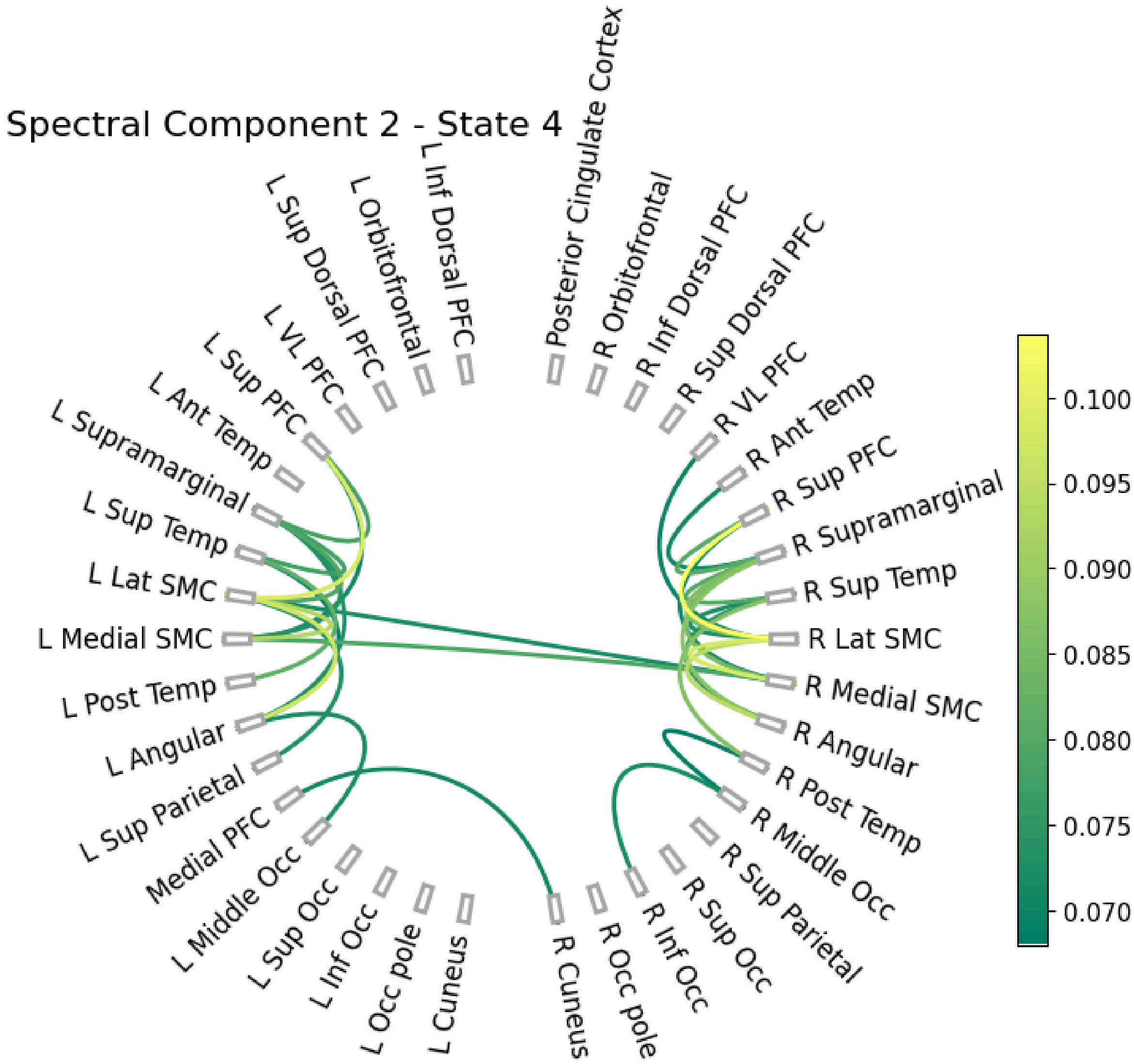
In [248…

```
connectivity_6states_SC2_S3 = thres_mean_c[1][2]  # comp 2 state 3

sc=1
title = 'Spectral Component 2 - State 3
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



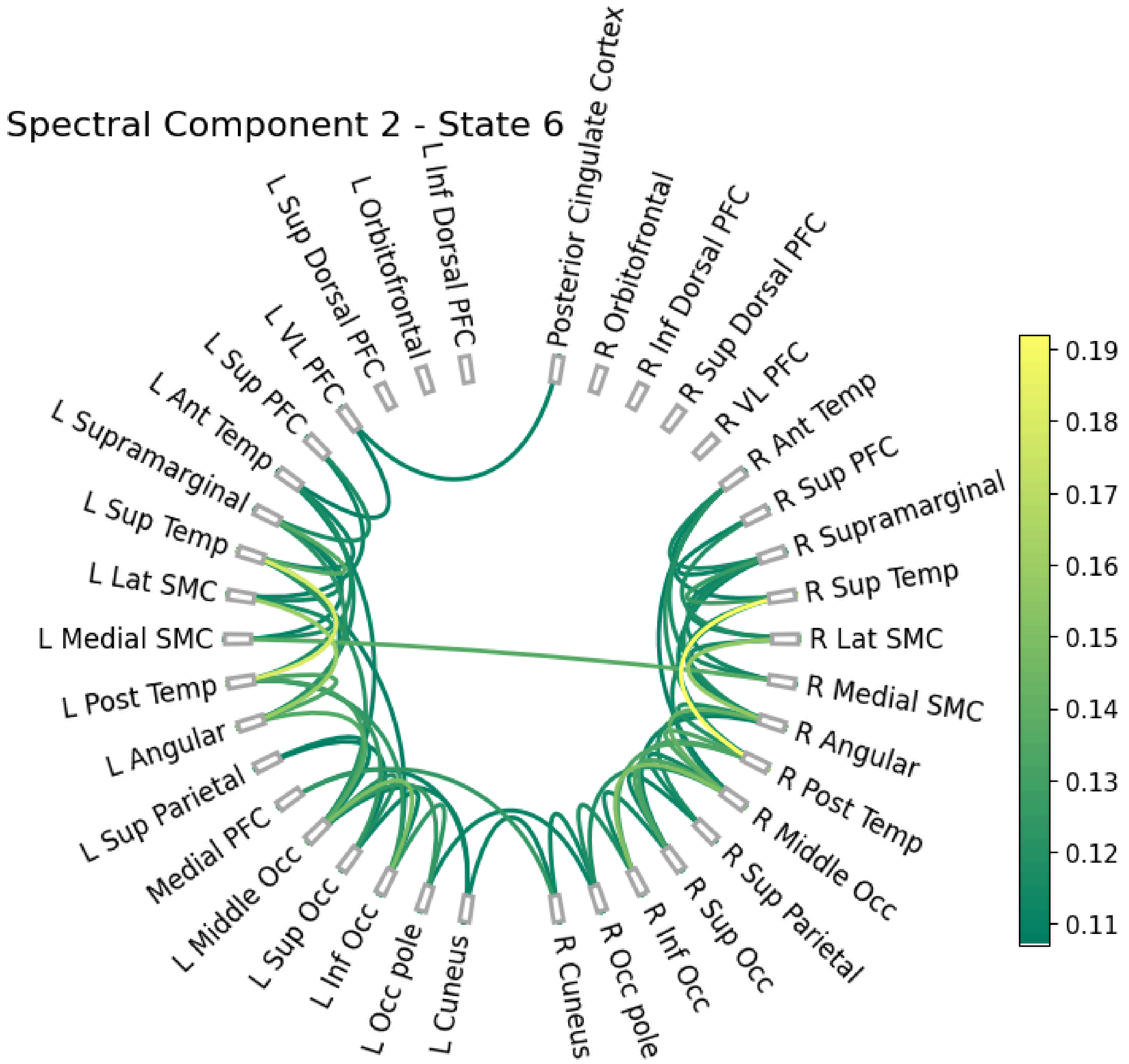
In [249…

```
connectivity_6states_SC2_S4 = thres_mean_c[1][3]  # comp 2 state 4

sc=1
title = 'Spectral Component 2 - State 4
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



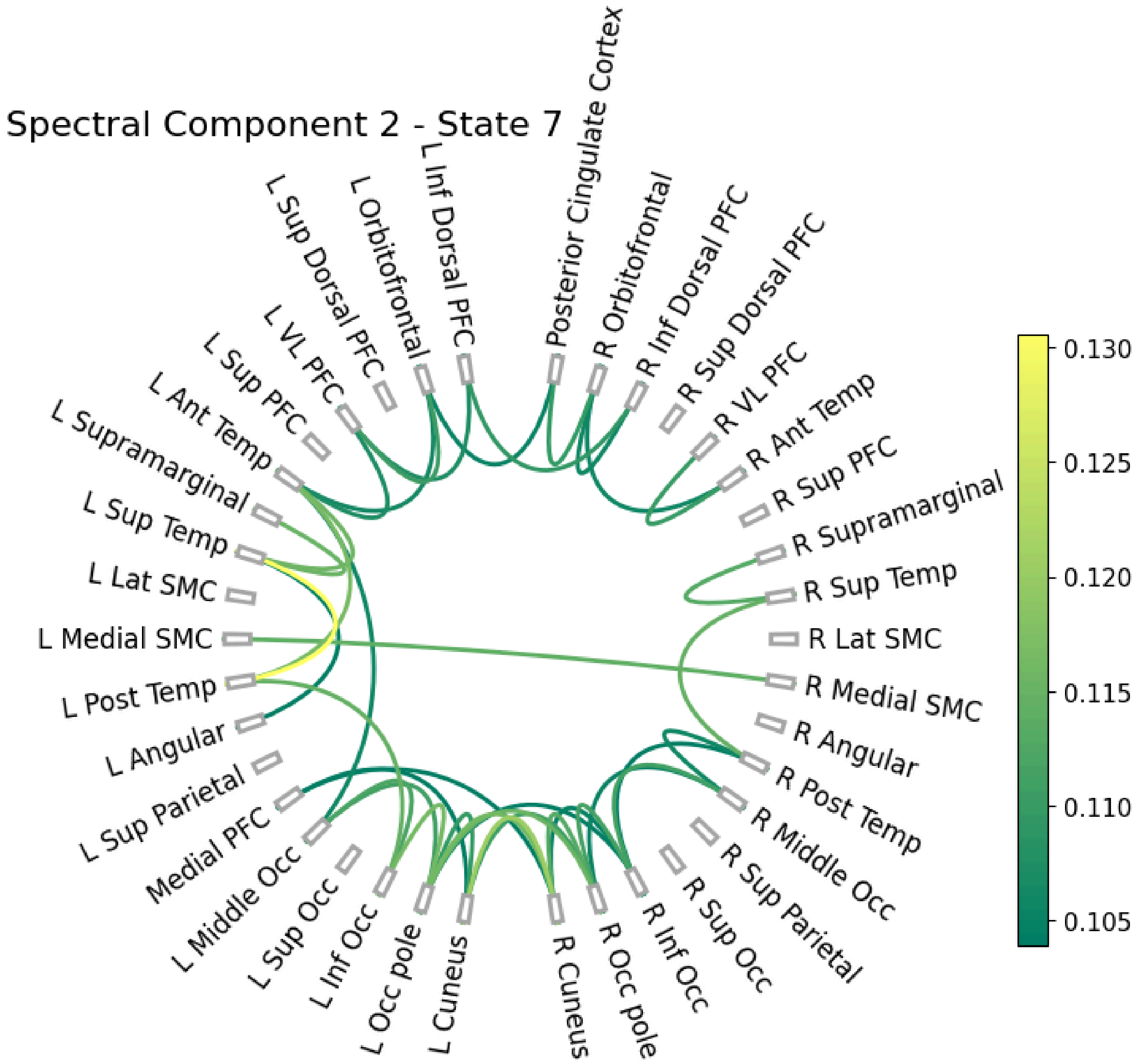
In [251…

```
connectivity_6states_SC2_S6 = thres_mean_c[1][4]  # comp 2 state 6

sc=1
title = 'Spectral Component 2 - State 6
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



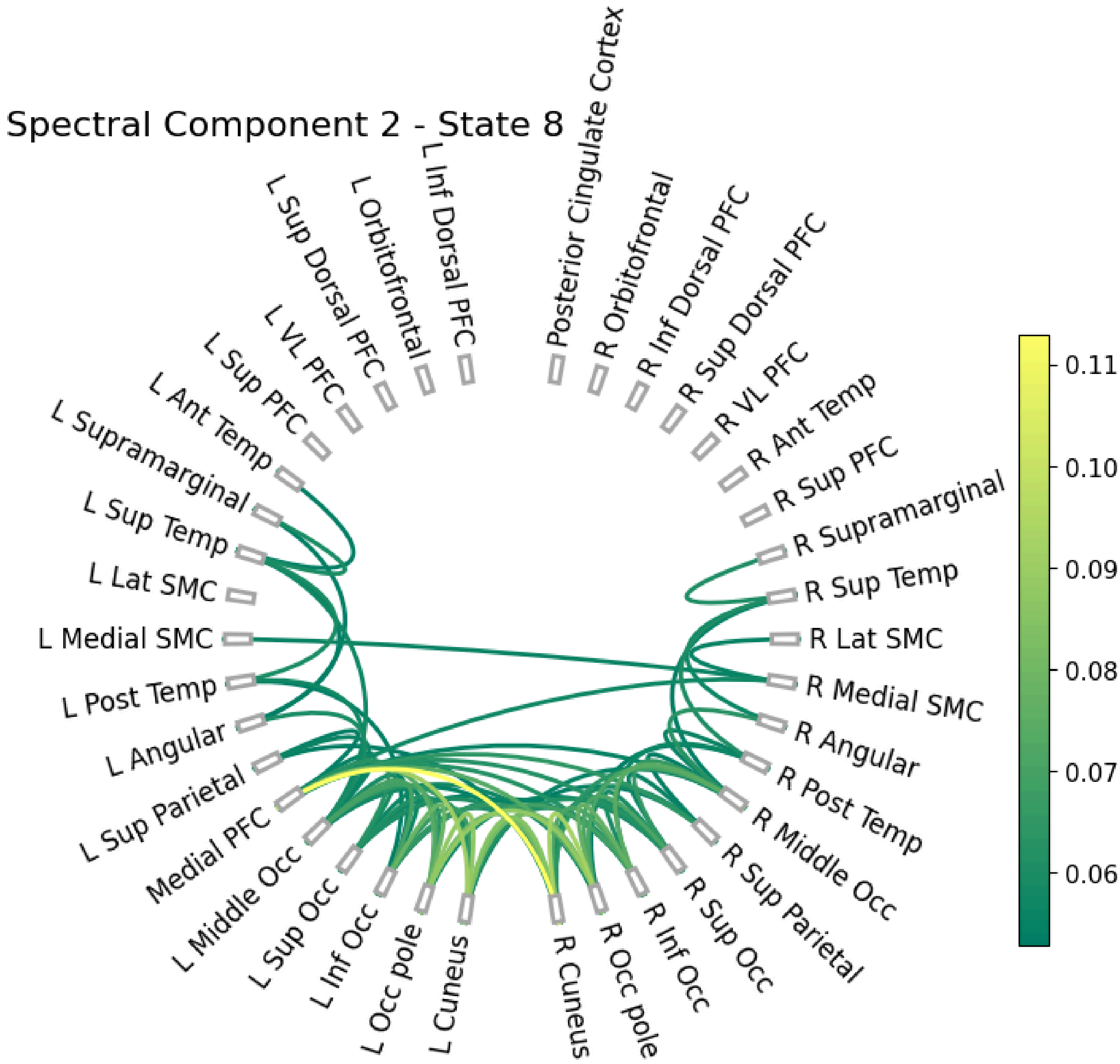
In [252…

```
connectivity_6states_SC2_S7 = thres_mean_c[1][5]  # comp 2 state 7

sc=1
title = 'Spectral Component 2 - State 7
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



In [253…

```
connectivity_6states_SC2_S8 = thres_mean_c[1][6]   # comp 2 state 8

sc=1
title = 'Spectral Component 2 - State 8
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC2_S
                              title=title, image_name=img_name, network=True
```



Spectral Component 3

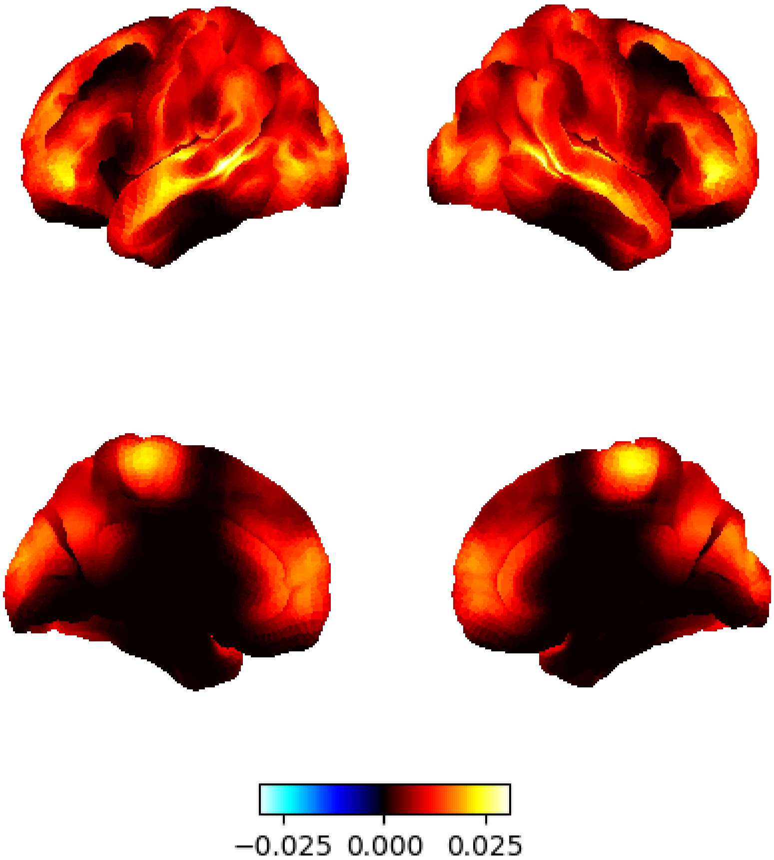
In [254…

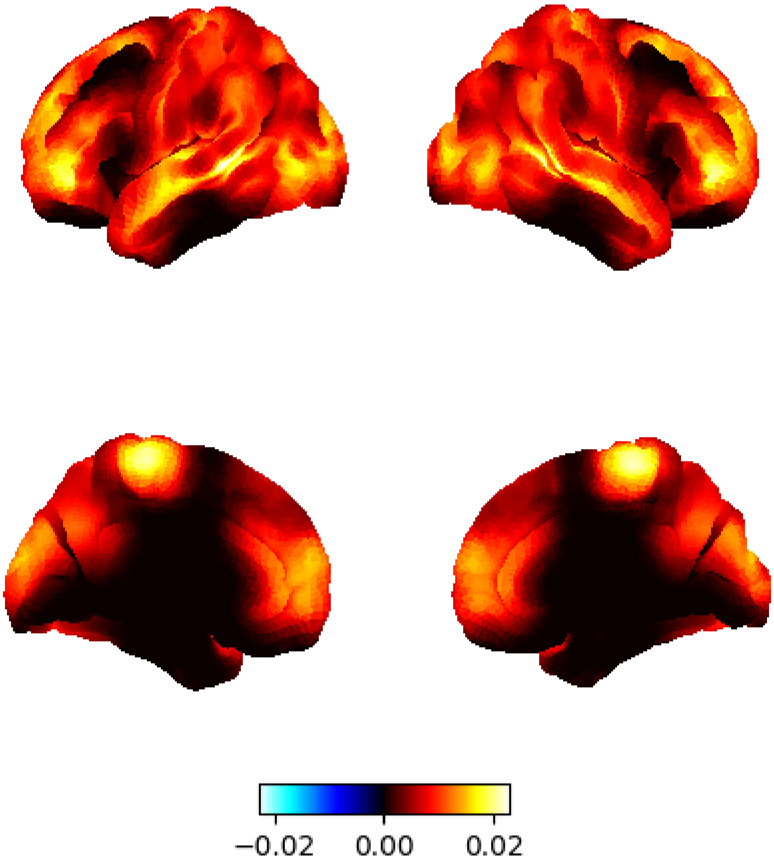
```
# Integrate the power spectra over a frequency range, weighted by the spectr
p_sc_all = power.variance_from_spectra(f, gpsd, wb_comp)
p_sc3 = p_sc_all[2]
```

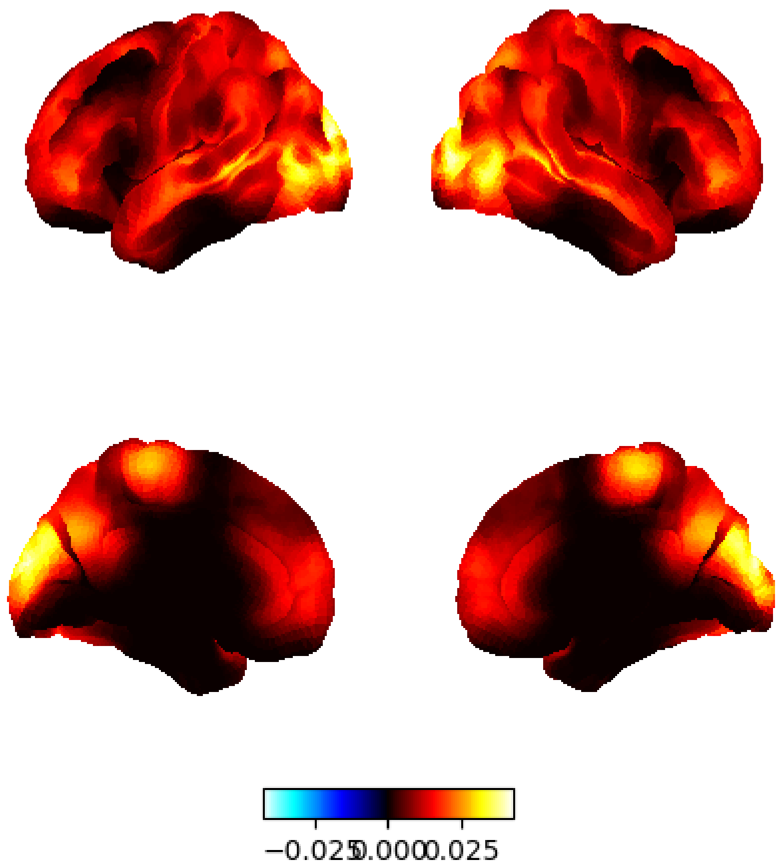
In [255…

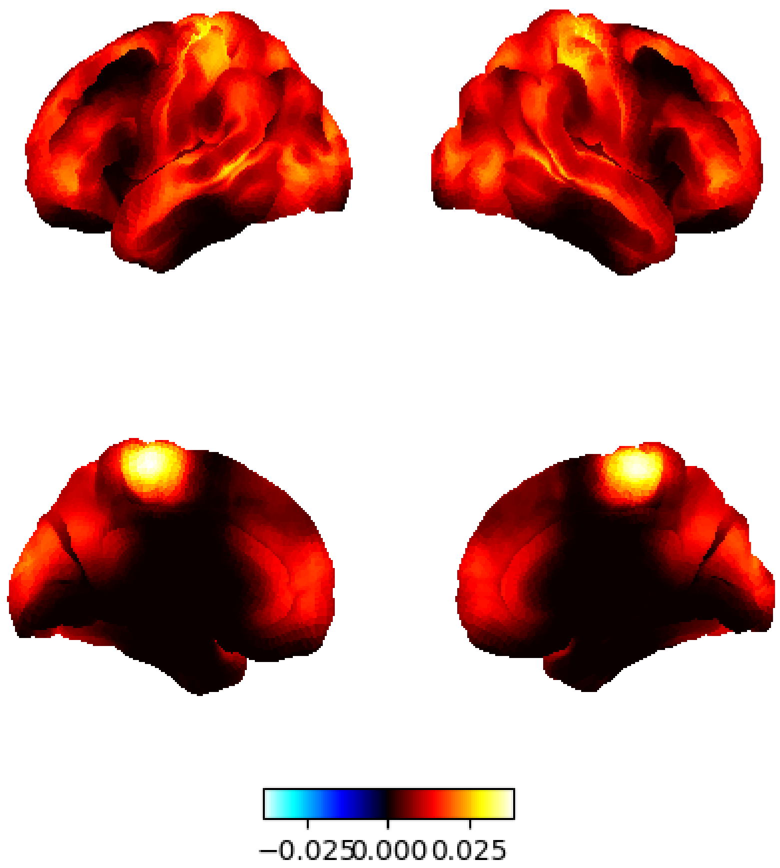
```
## Plotting power maps (averages over all subjects) per state
fig, ax = power.save(
    p_sc3,
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
)
```

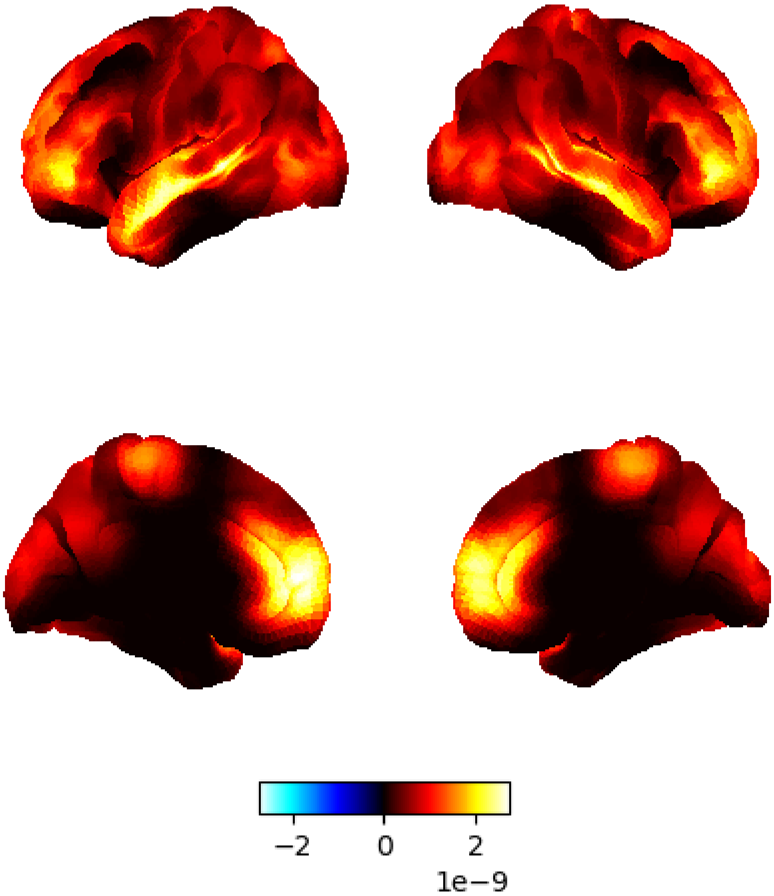
```
Saving images: 100%|██████████| 8/8 [00:09<00:00,  1.15s/it]
```

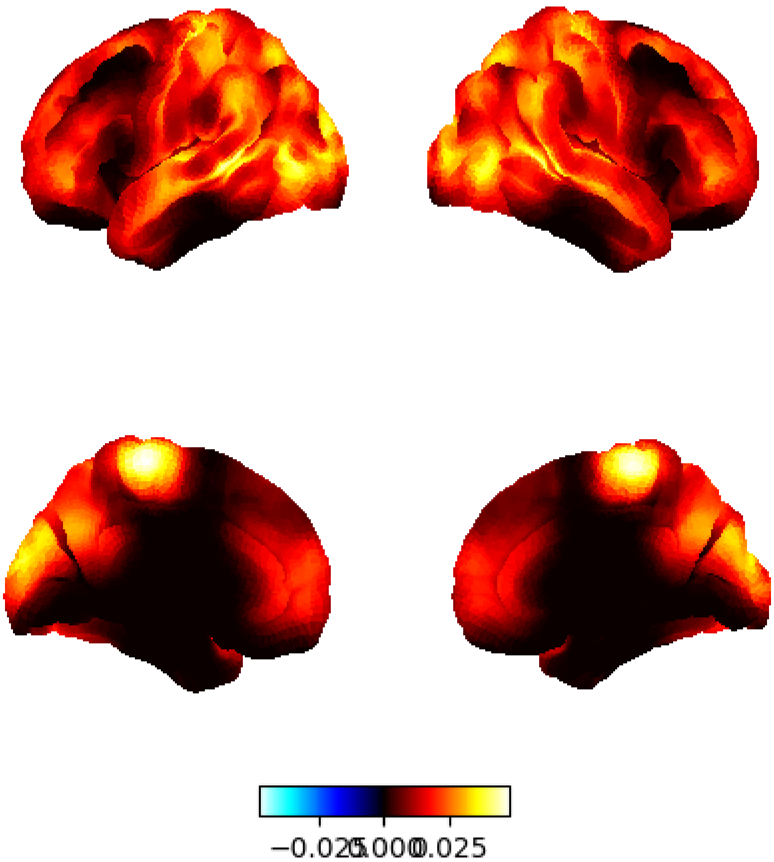

−0.025 0.000 0.025

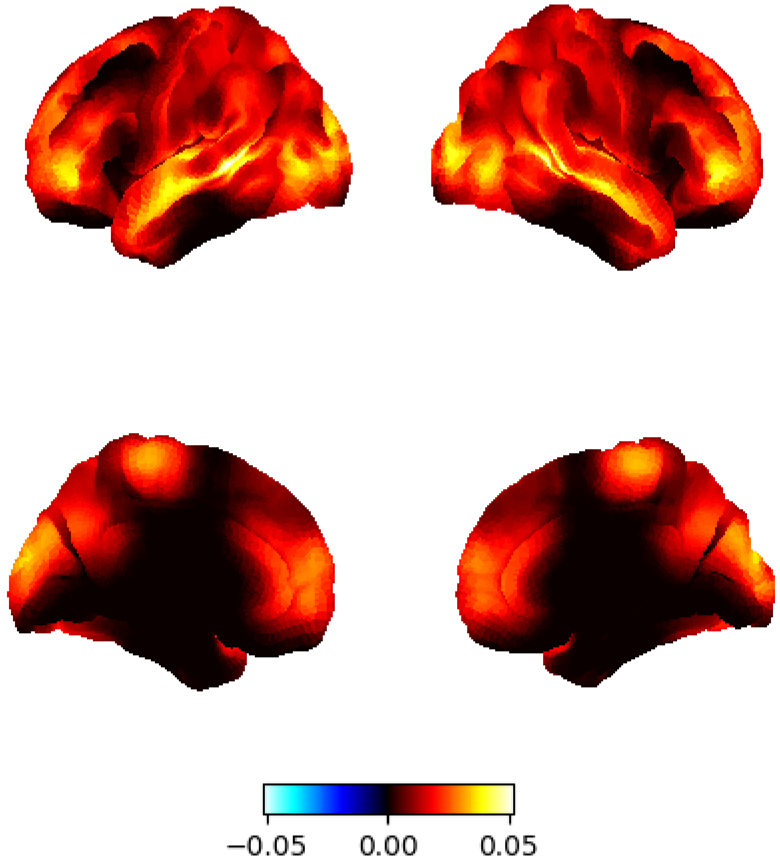

−0.02 0.00 0.02

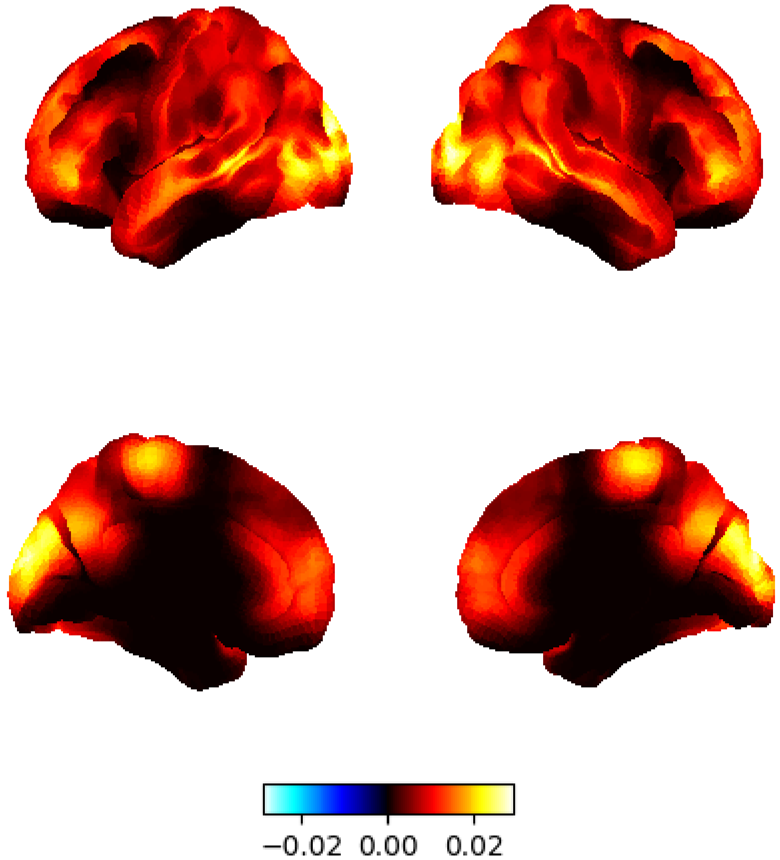

−0.025
0.000
0.025


−0.025
0.000
0.025


−2
0
2
1e−9


−0.025
0.000
0.025



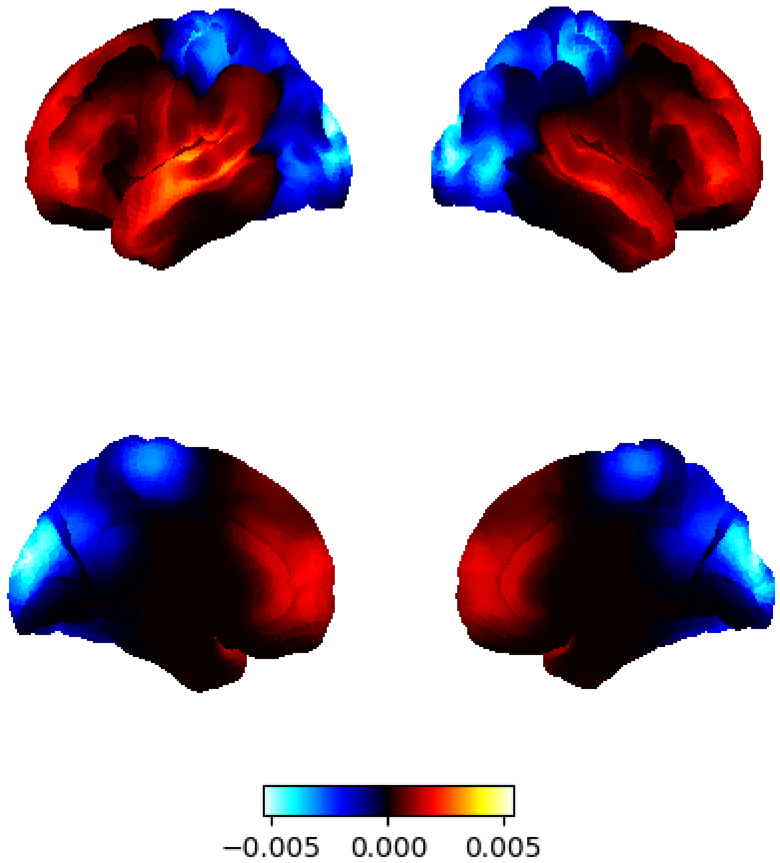


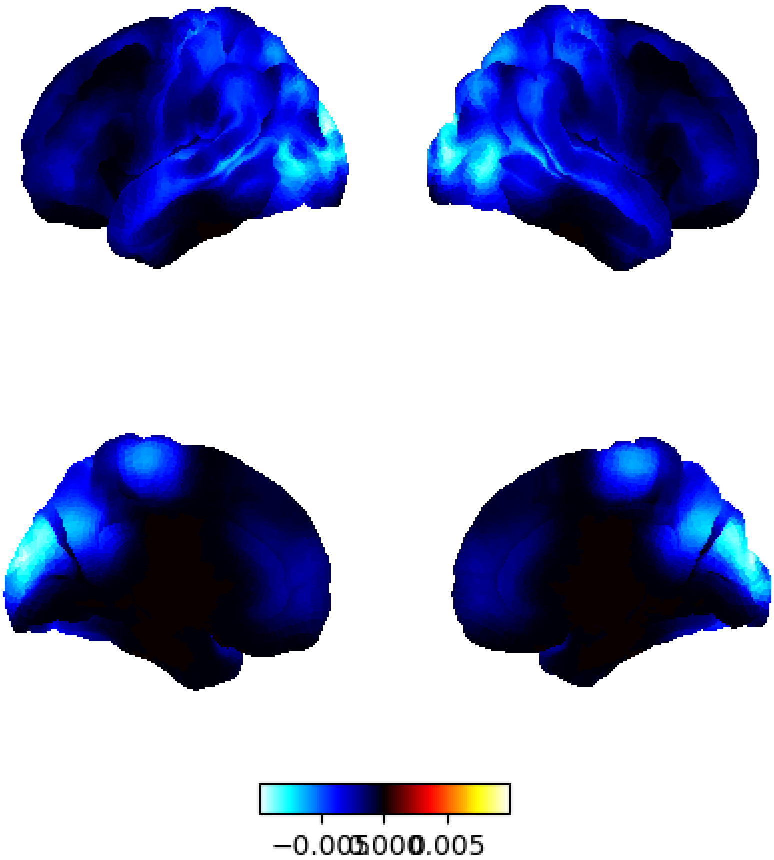
Plot **relative** to something else (by **substracting the mean**)

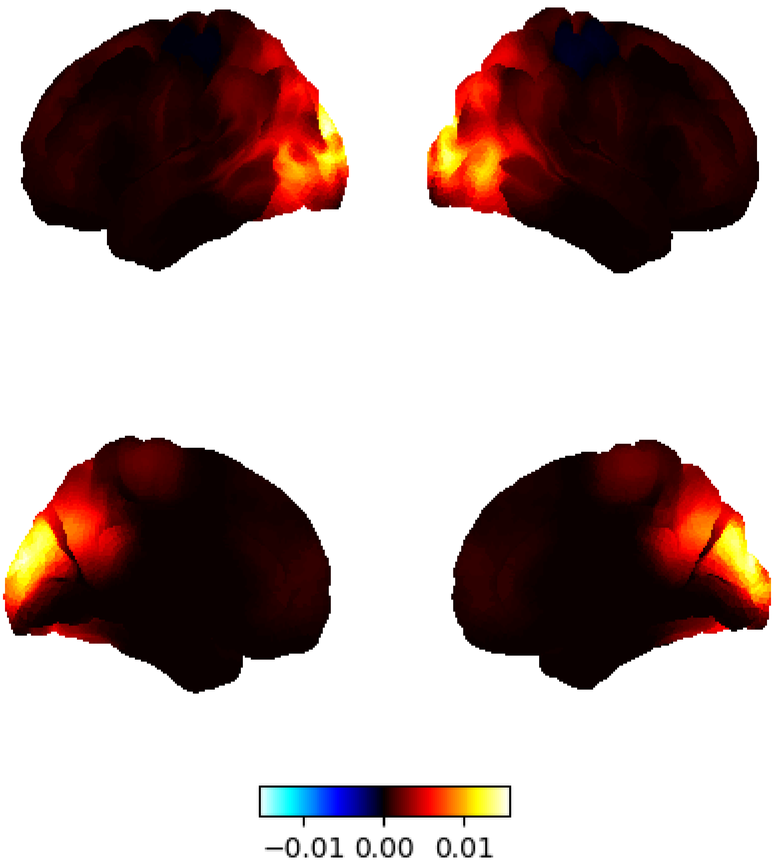
In [256…

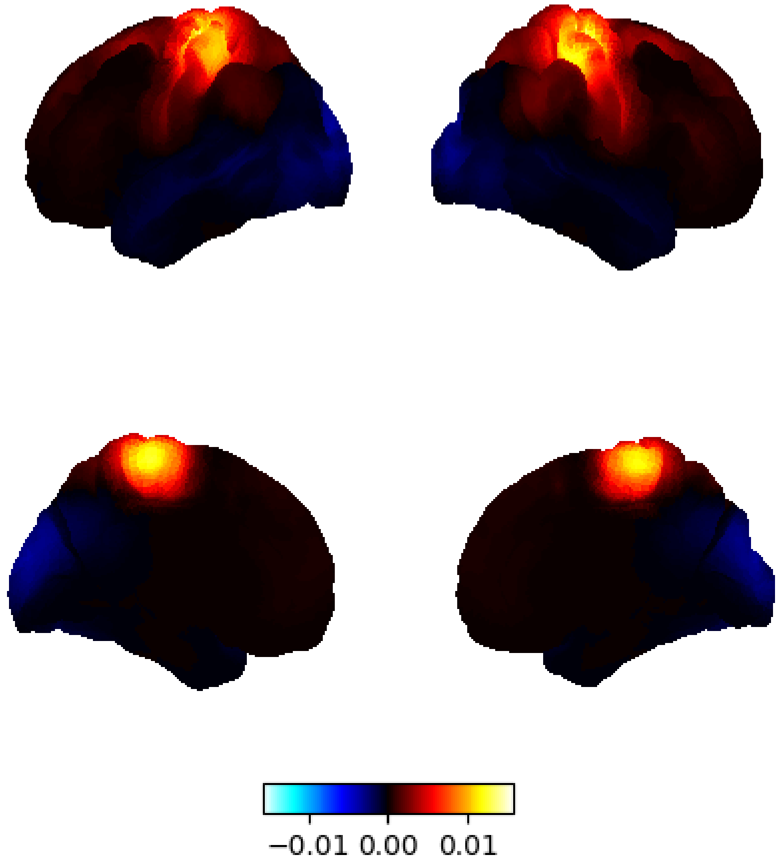
```
# Takes a few seconds for the power maps to appear
fig, ax = power.save(
    p_sc3,
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
    subtract_mean=True,
)
```

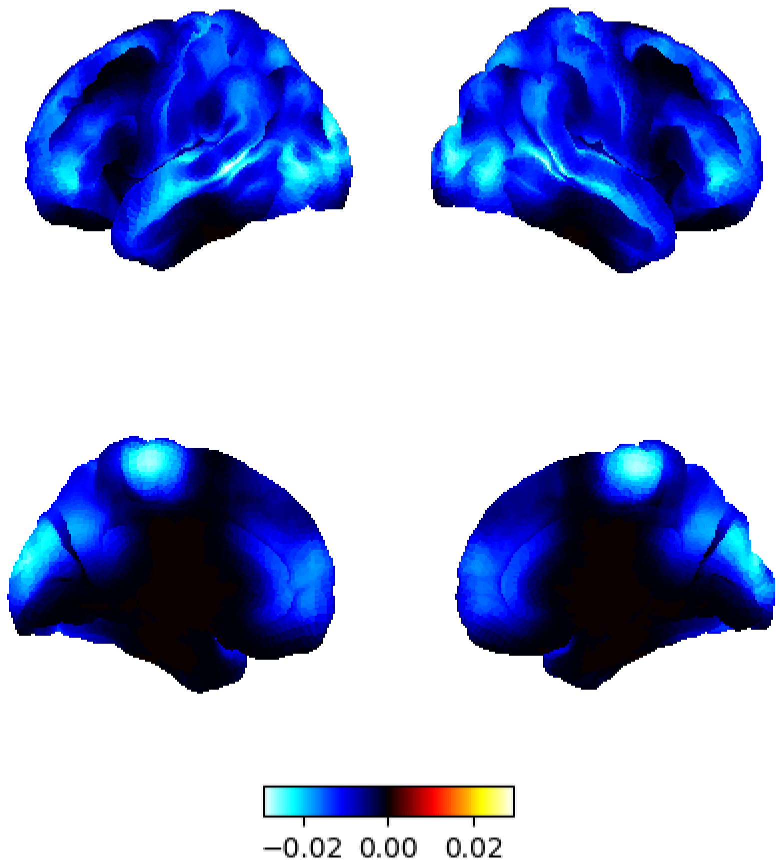
```
Saving images: 100%|██████████| 8/8 [00:08<00:00,  1.12s/it]
```

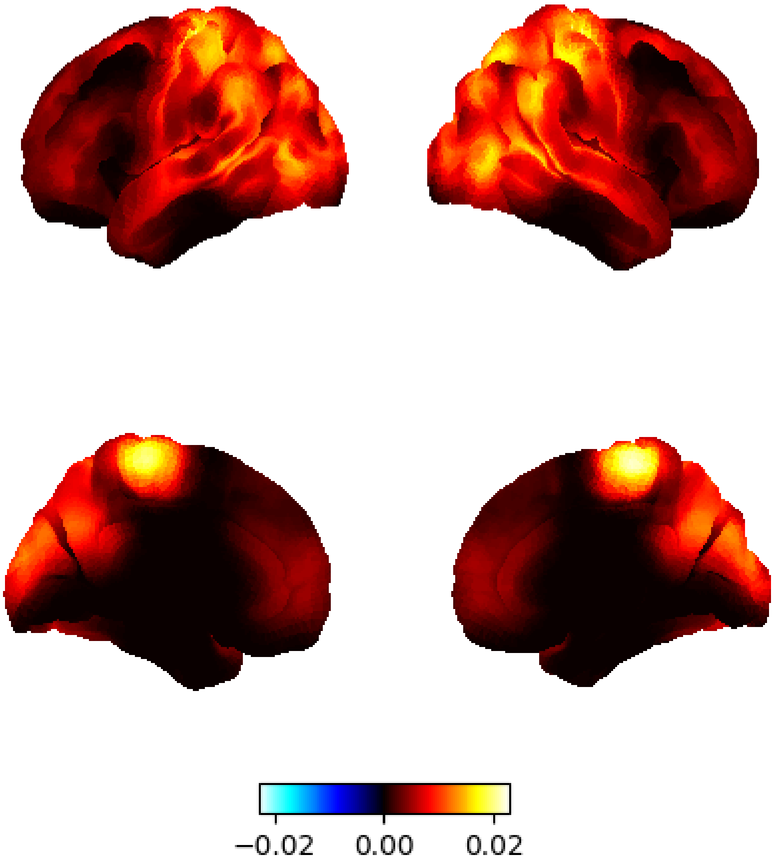


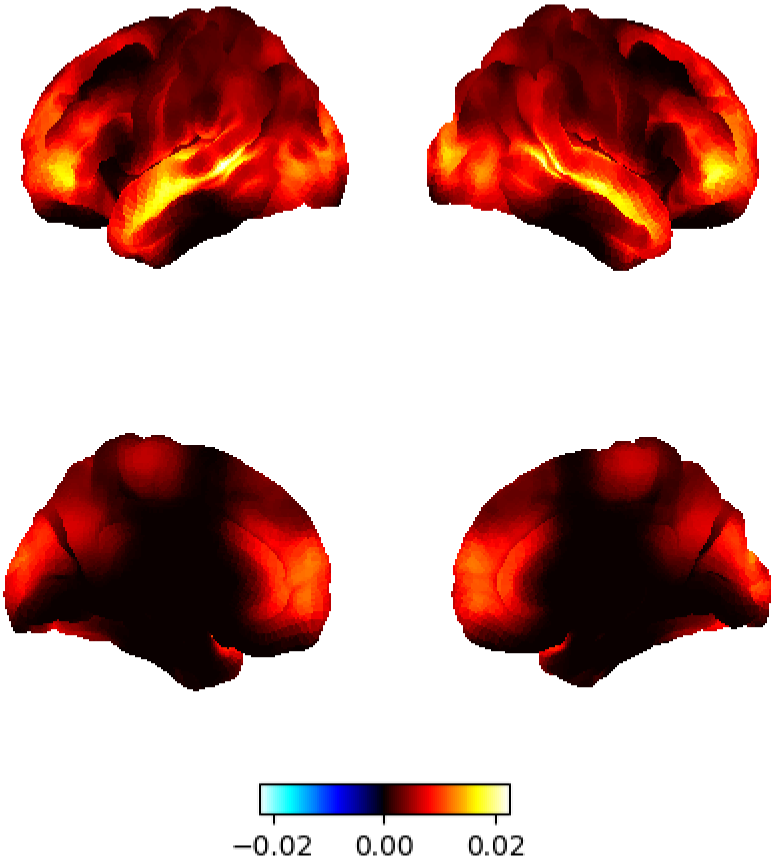

−0.005
0.000
0.005

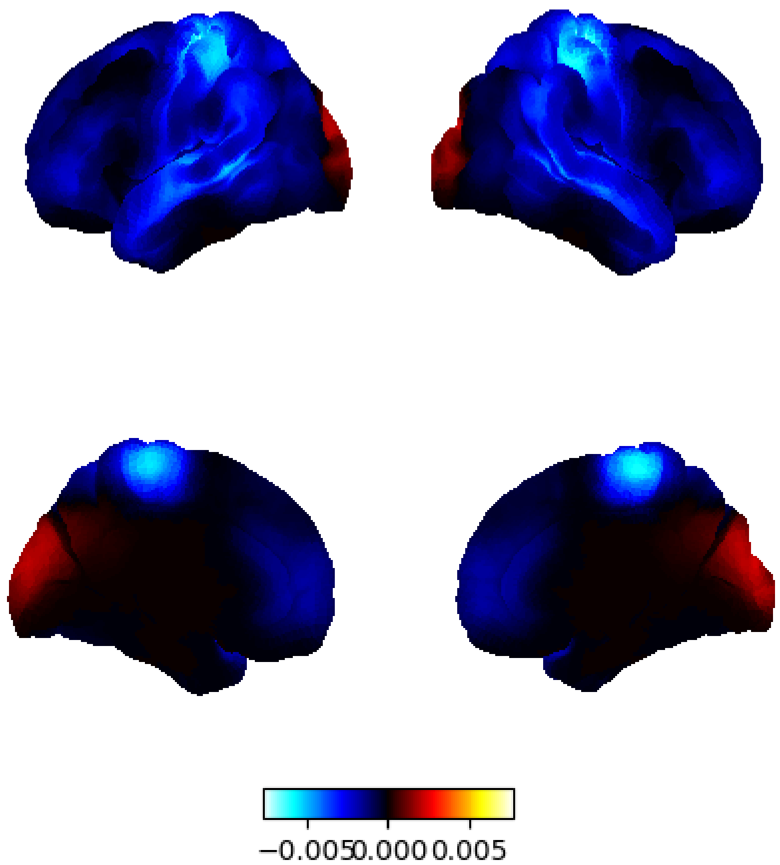

−0.01
0.00
0.01


−0.01 0.00 0.01


−0.02 0.00 0.02


−0.02
0.00
0.02


−0.02
0.00
0.02

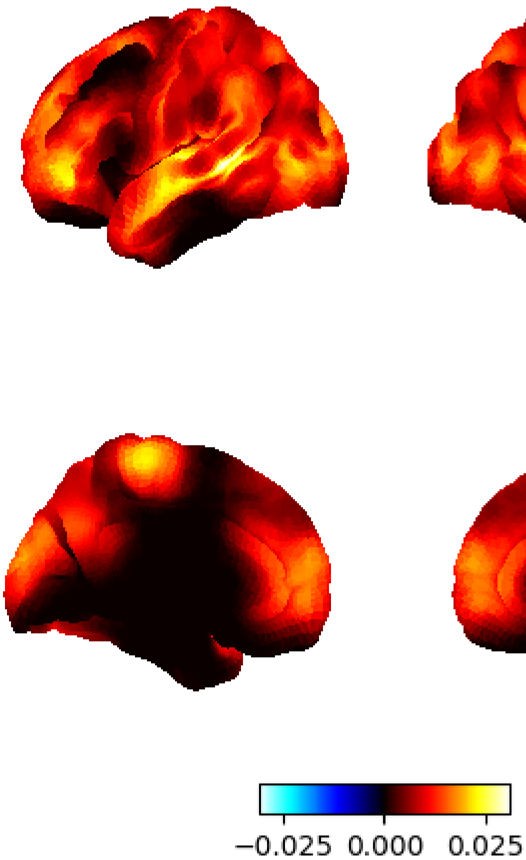


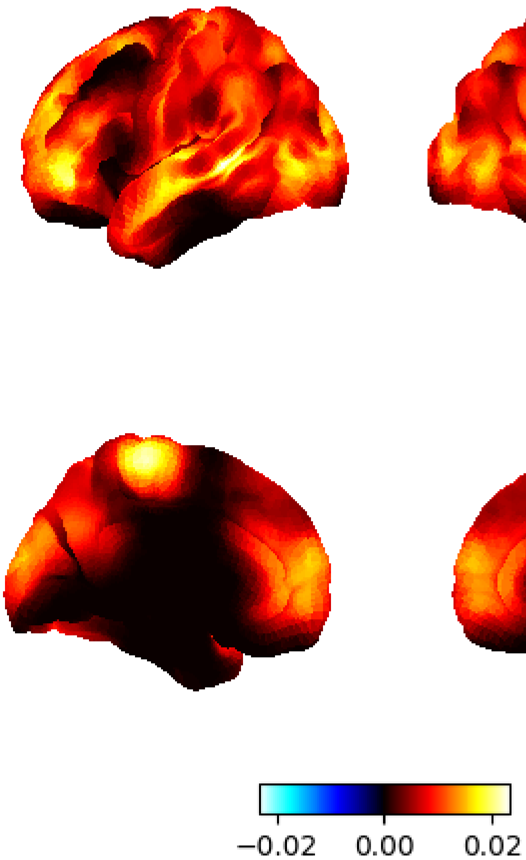
Group analysis

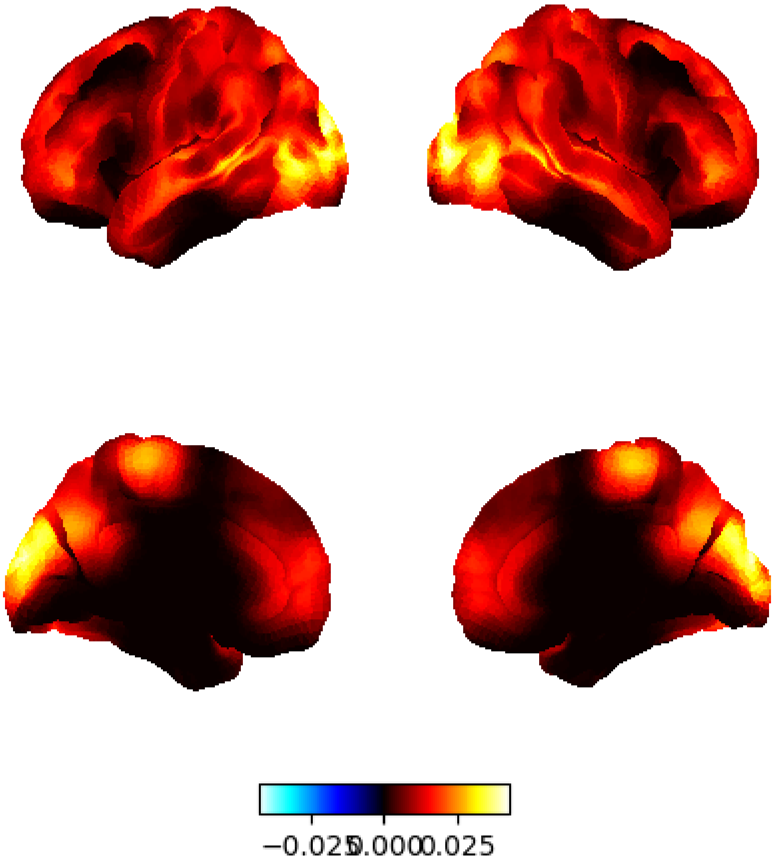
In [257…

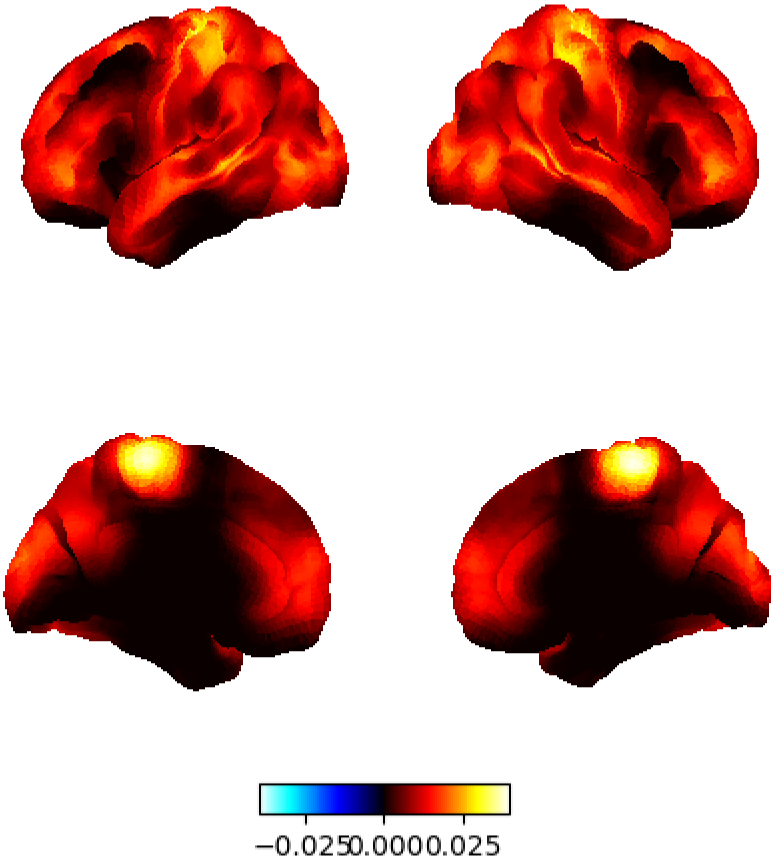
```
# Get the power arrays for group 1
p_sc3_control = power.variance_from_spectra(f, psd, wb_comp)[df_control_idx,

# Get the power arrays for group 2
p_sc3_ms = power.variance_from_spectra(f, psd, wb_comp)[df_ms_idx,2]


# Group means
p_sc3_control_mean = np.mean(p_sc3_control,axis=0)
p_sc3_ms_mean = np.mean(p_sc3_ms,axis=0)

print(np.shape(p_sc3_control))
print(np.shape(p_sc3_control_mean))

# Plot (it takes a few seconds for the brain maps to be shown)
fig, ax = power.save(
    [p_sc3_control_mean, p_sc3_ms_mean],
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
)
```

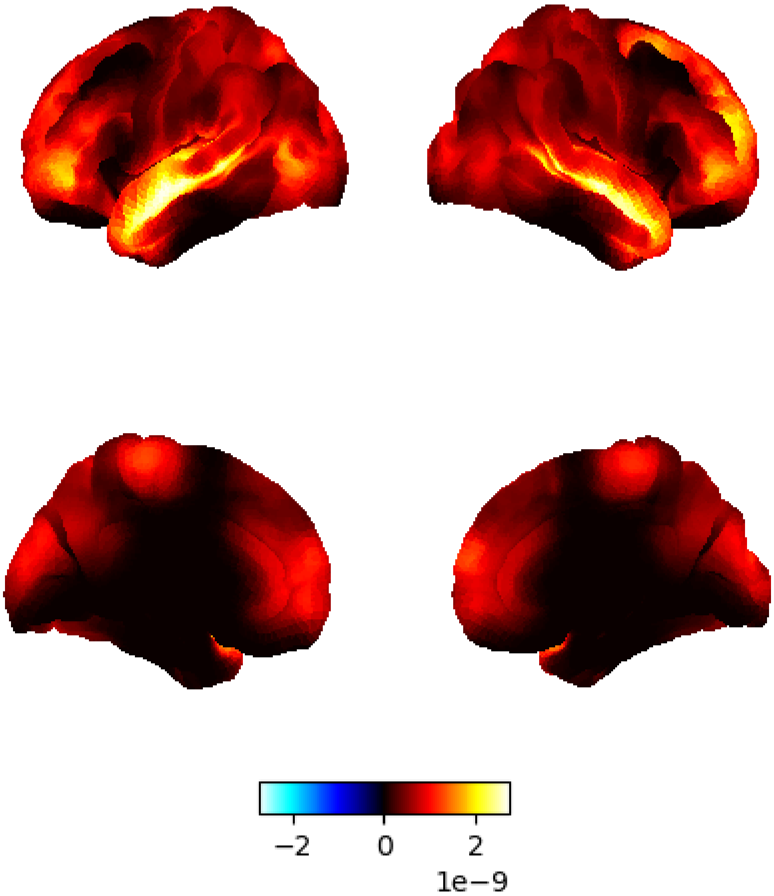
```
(37, 8, 38)
(8, 38)
Saving images: 100%|██████████| 8/8 [00:08<00:00,  1.12s/it]
```

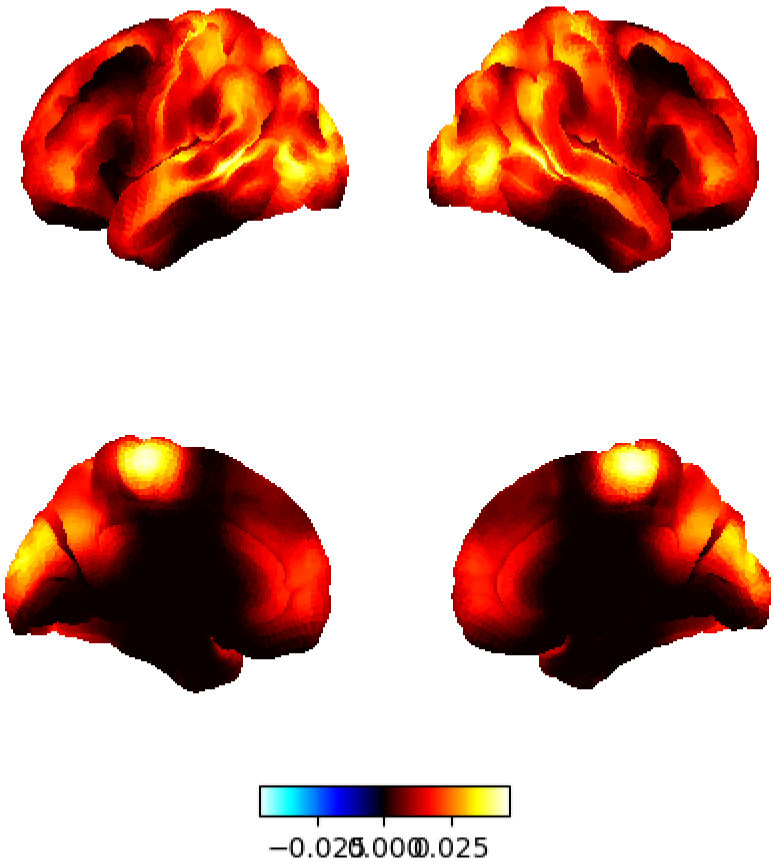

−0.025 0.000 0.025

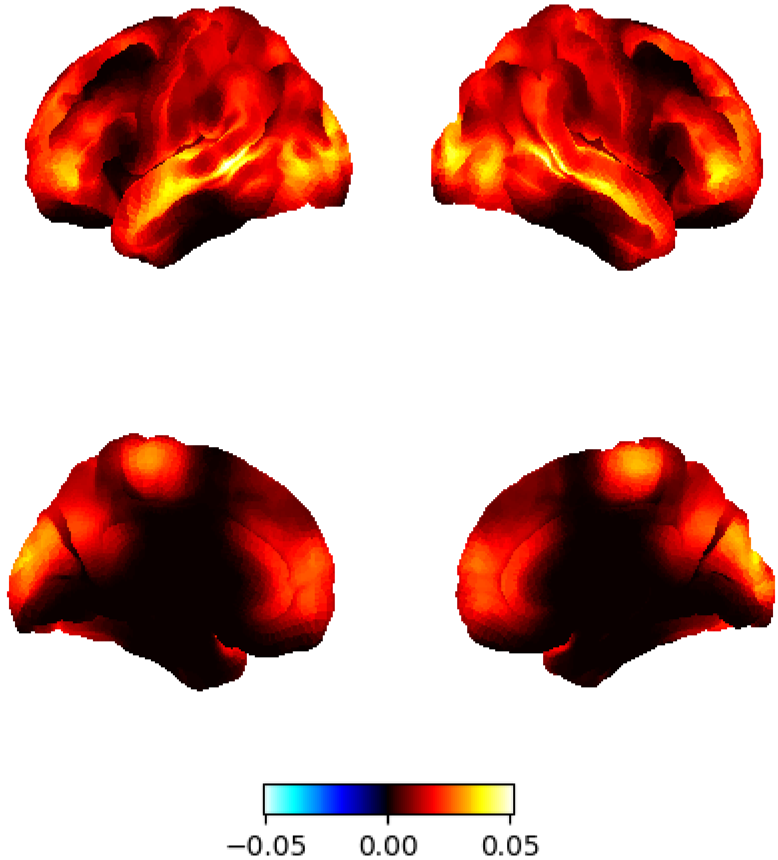

−0.02 0.00 0.02

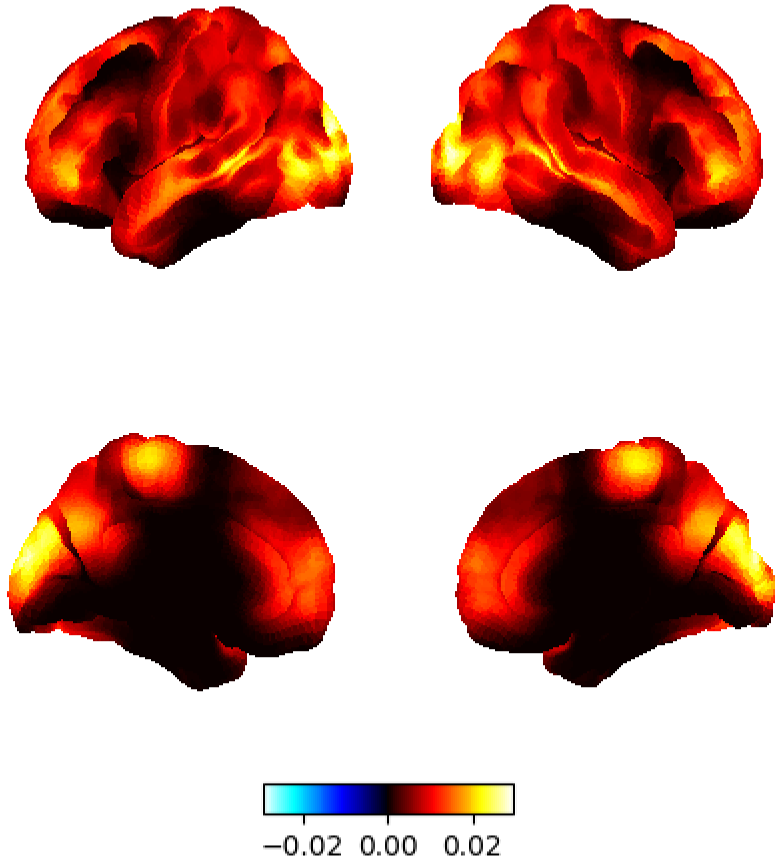

−0.025
0.000
0.025


−0.025
0.000
0.025


−2
0
2
1e−9


−0.025
0.000
0.025



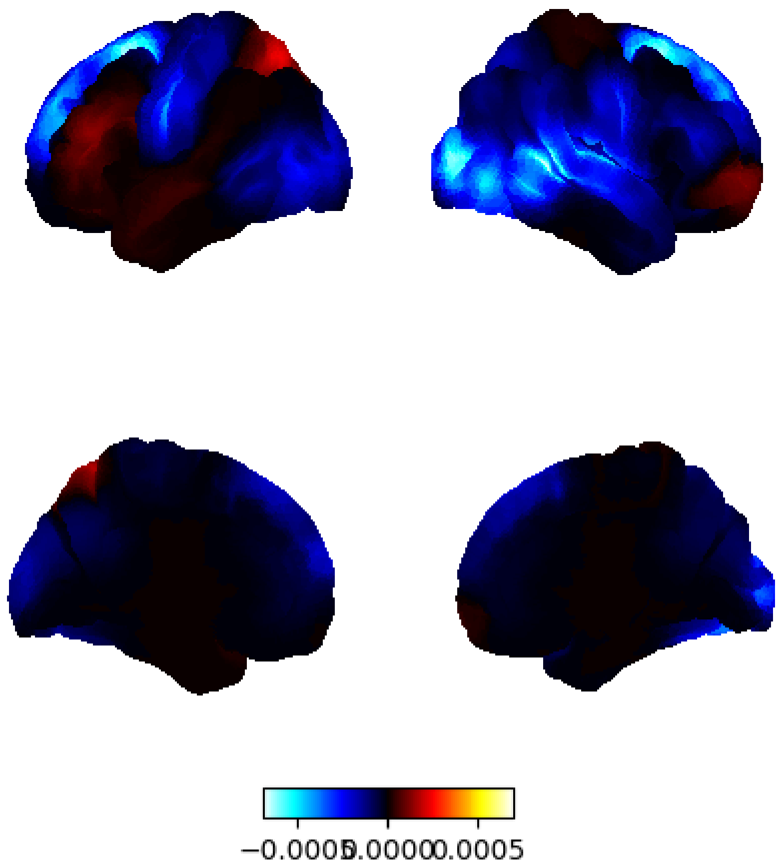


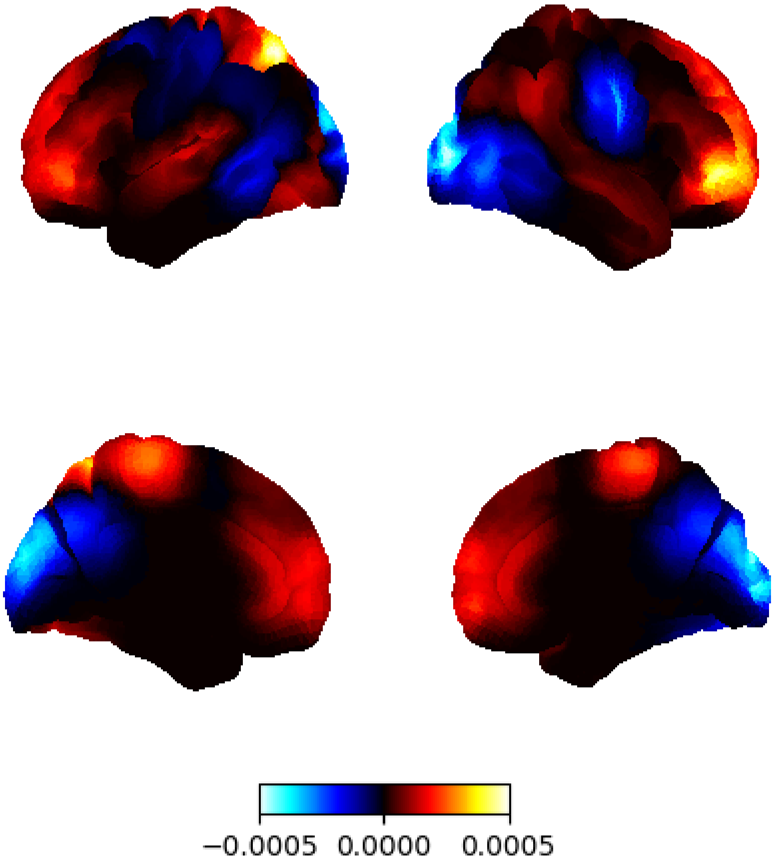
Plot the **diffference between the 2 groups**

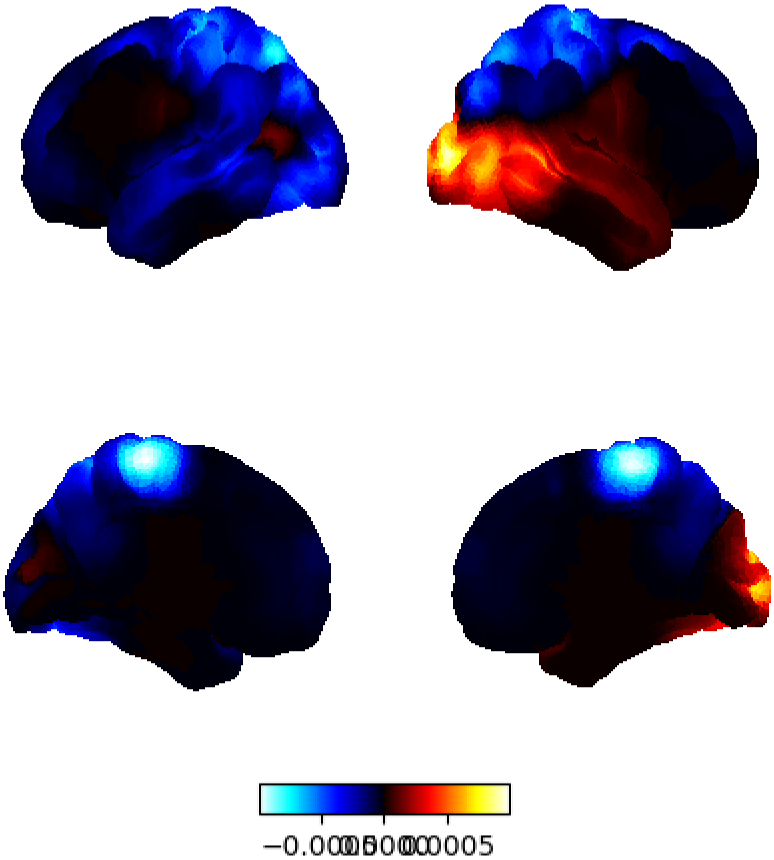
In [258…

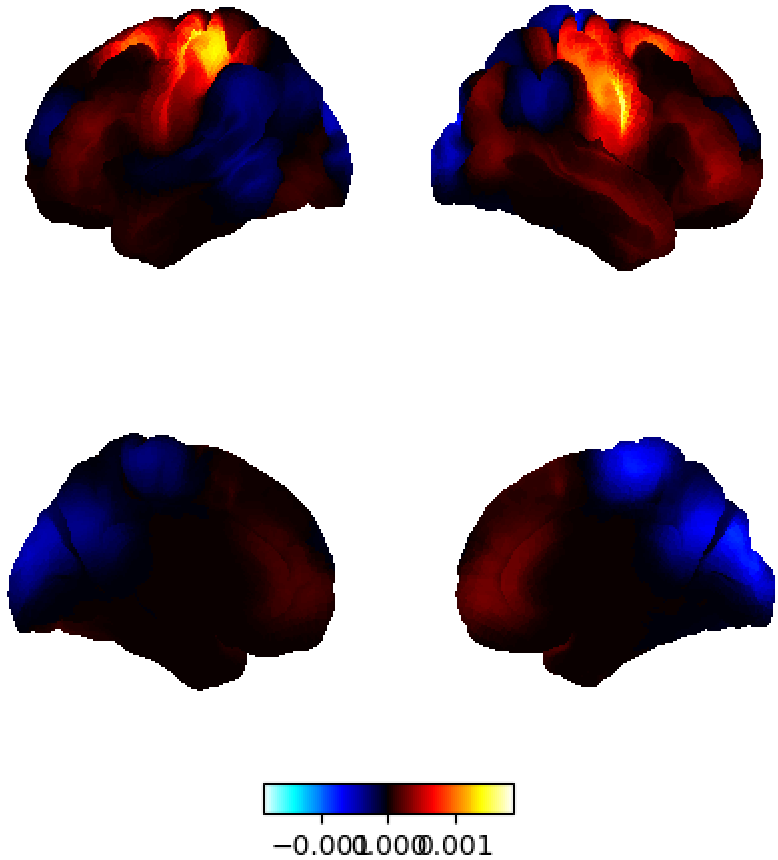
```
# Calculate the difference in power between the groups
p_diff = p_sc3_control_mean - p_sc3_ms_mean

# Plot
fig, ax = power.save(
    p_diff,
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
)
```

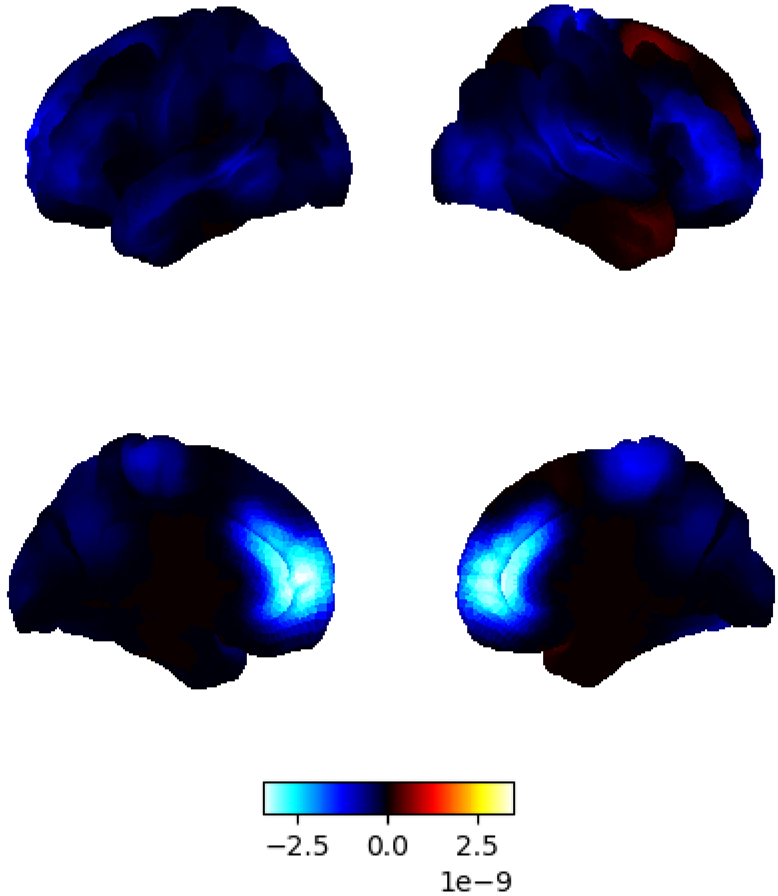
```
Saving images: 100%|██████████| 8/8 [00:08<00:00,  1.07s/it]
```

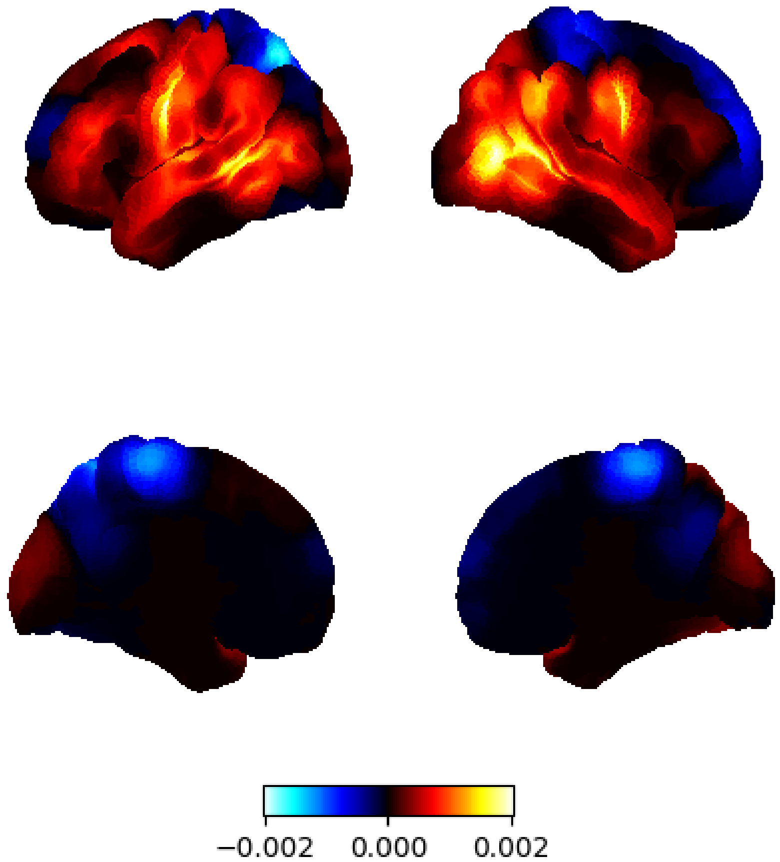


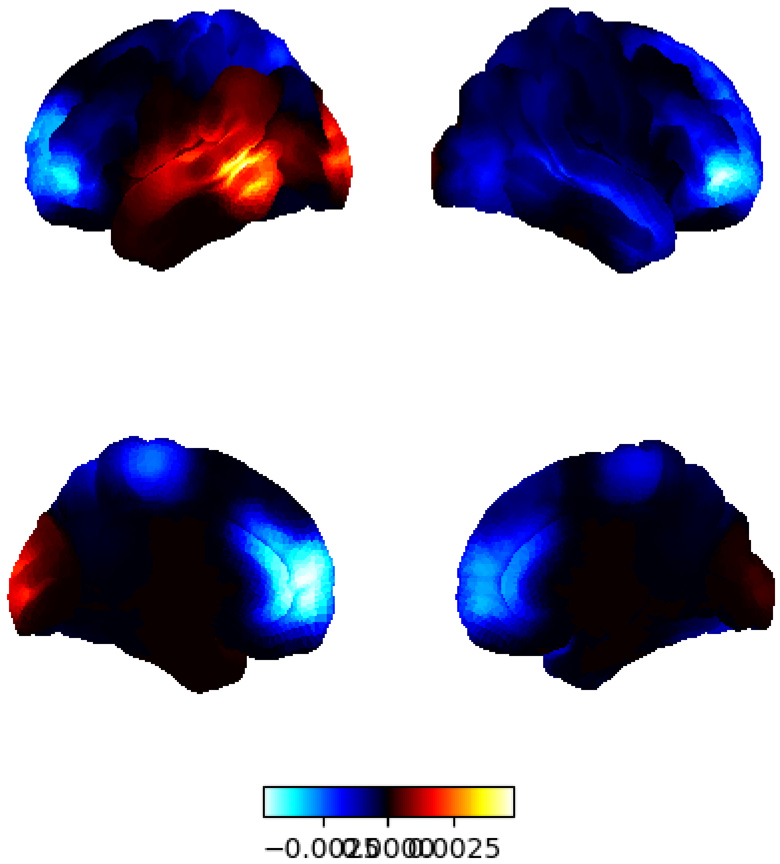

−0.0005
0.0000
0.0005

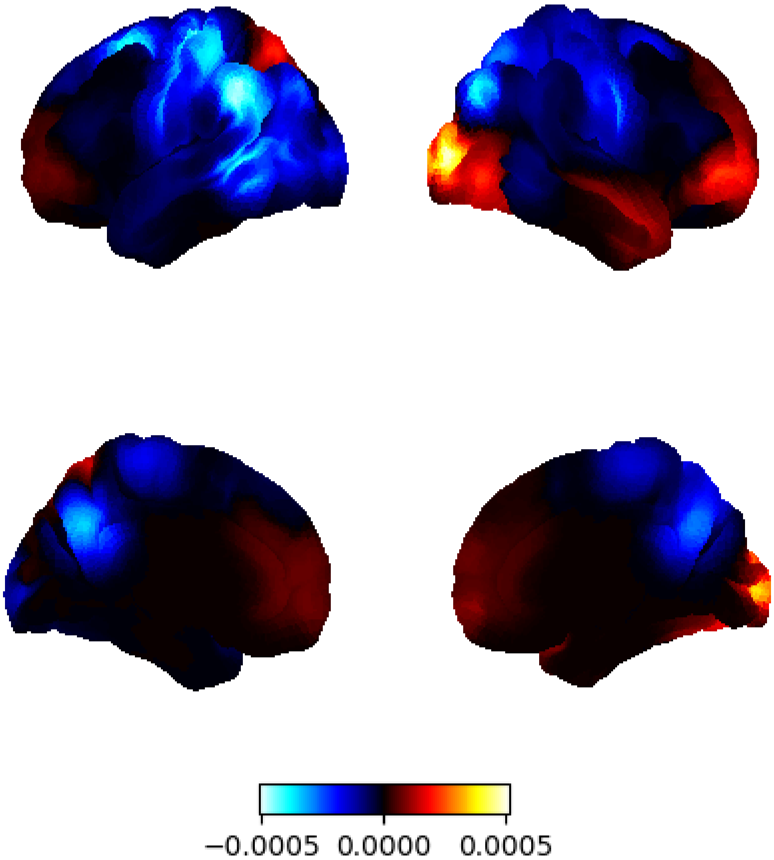



−0.001
0.000
0.001


−2.5
0.0
2.5
1e−9


−0.002
0.000
0.002


−0.0025
0.0000
0.0025



Statistical significance testing

HC vs. MS

In [259…

```
from osl_dynamics.analysis import statistics

# Group assignments
## use assignments variable defined in the section of the Summary Statistics
p_sc3_gd = power.variance_from_spectra(f, psd, wb_comp)[:,2]

# Do significant testing
diff, pvalues = statistics.group_diff_max_stat_perm(
    p_sc3_gd,
    assignments,
    n_perm=500,
)

# Do we have any significant parcels?
print("Number of significant parcels:", np.sum(pvalues < 0.05))
```

```
Permuting contrast <class 'glmtools.design.Contrast'>(GroupDiff,Differentia
l) with mode=row-shuffle
        Computing 500 permutations
        Taking max-stat across ['features 1', 'features 2'] dimensions
Using tstats as metric
Number of significant parcels: 0
```

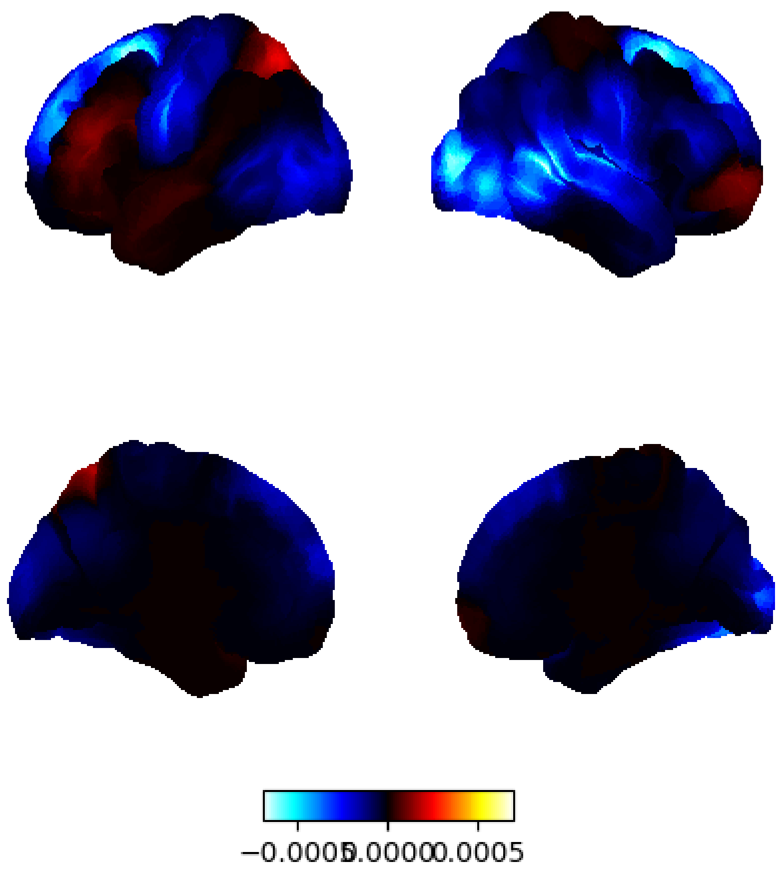
If you have parcels with a significant difference in power between groups:

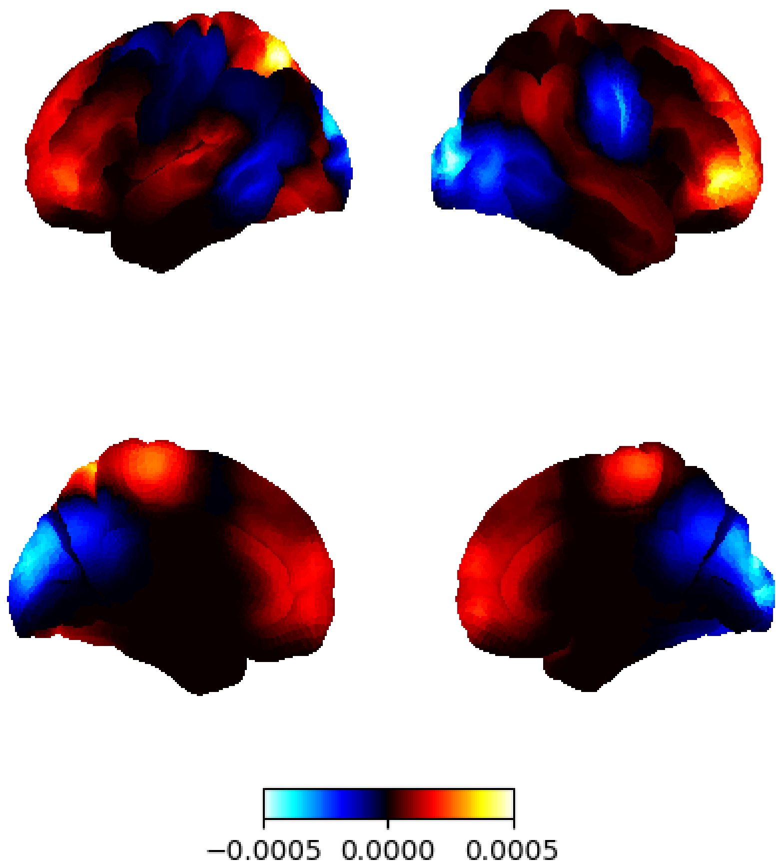
In [260…

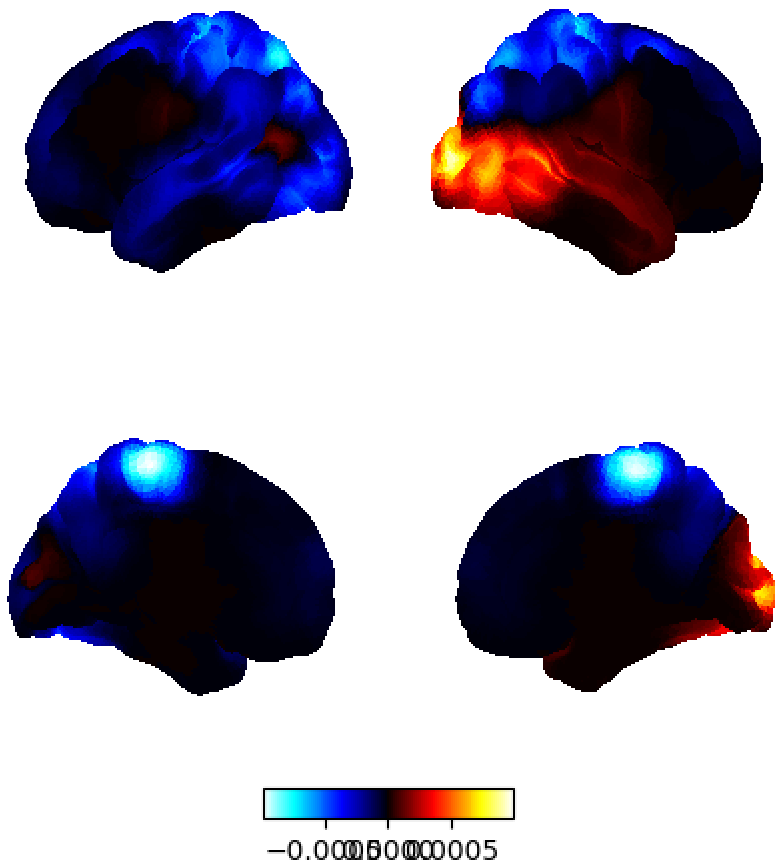
```
# Zero non-significant parcels
diff_sig = diff.copy()
```

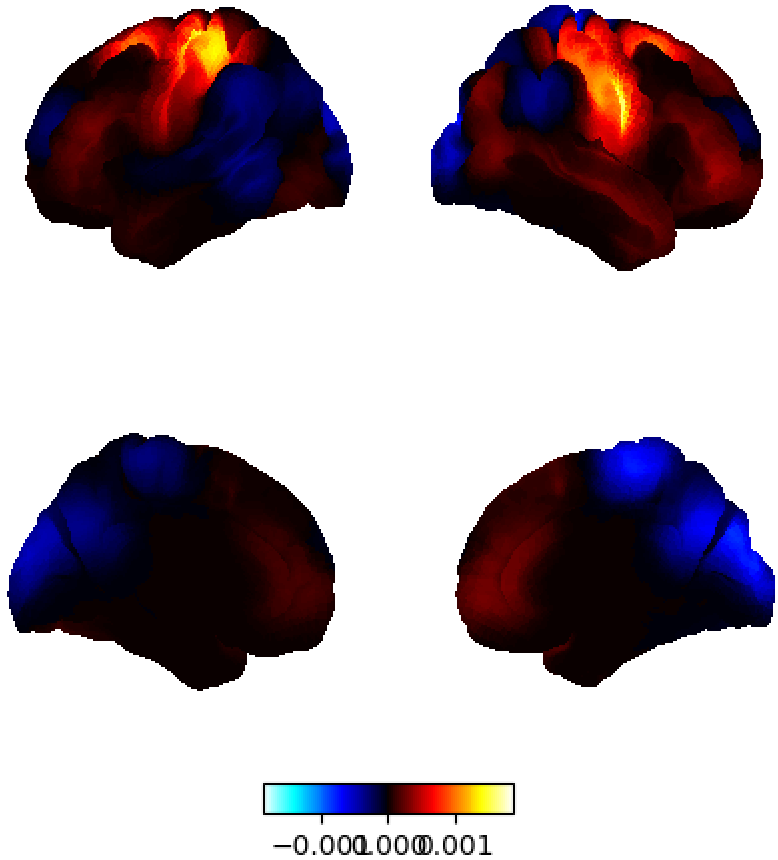
```
diff_sig[pvalues < 0.05] = 0

# Plot
fig, ax = power.save(
    diff_sig,
    mask_file="/home/fakbaria/osl/std_masks/MNI152_T1_8mm_brain.nii.gz",
    parcellation_file="/home/olivierb/38_parcels.nii",
)
```

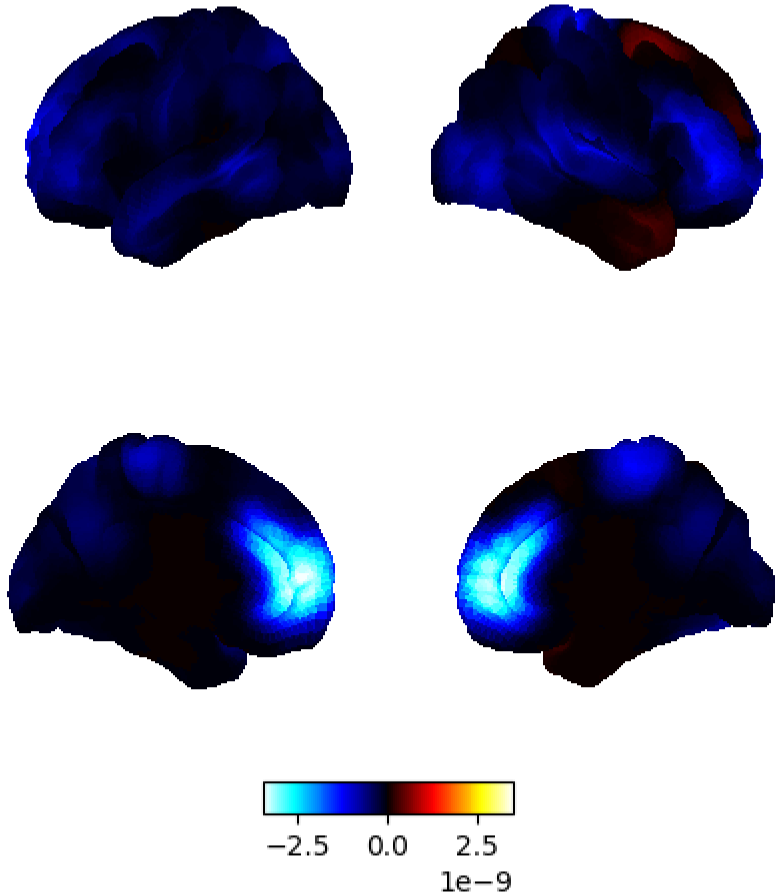
```
Saving images: 100%|██████████| 8/8 [00:08<00:00,  1.12s/it]
```

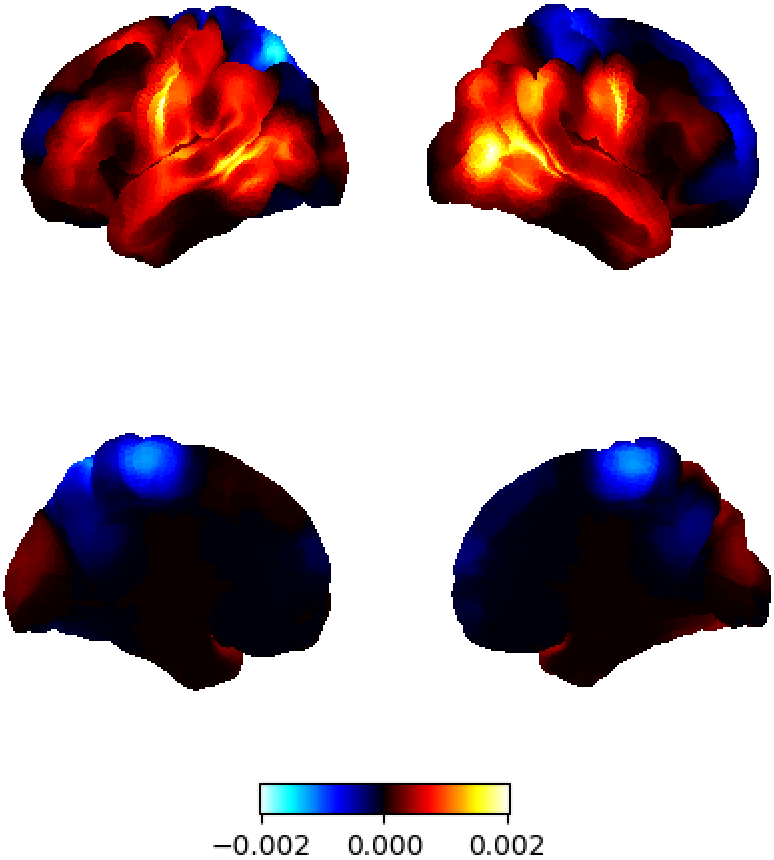


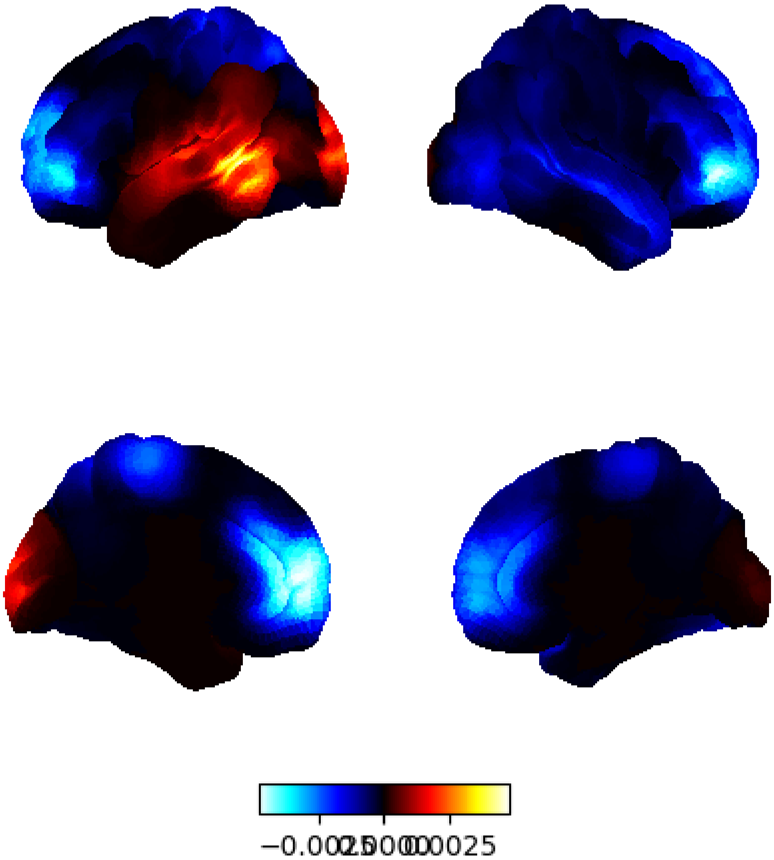

−0.0005
0.0000
0.0005

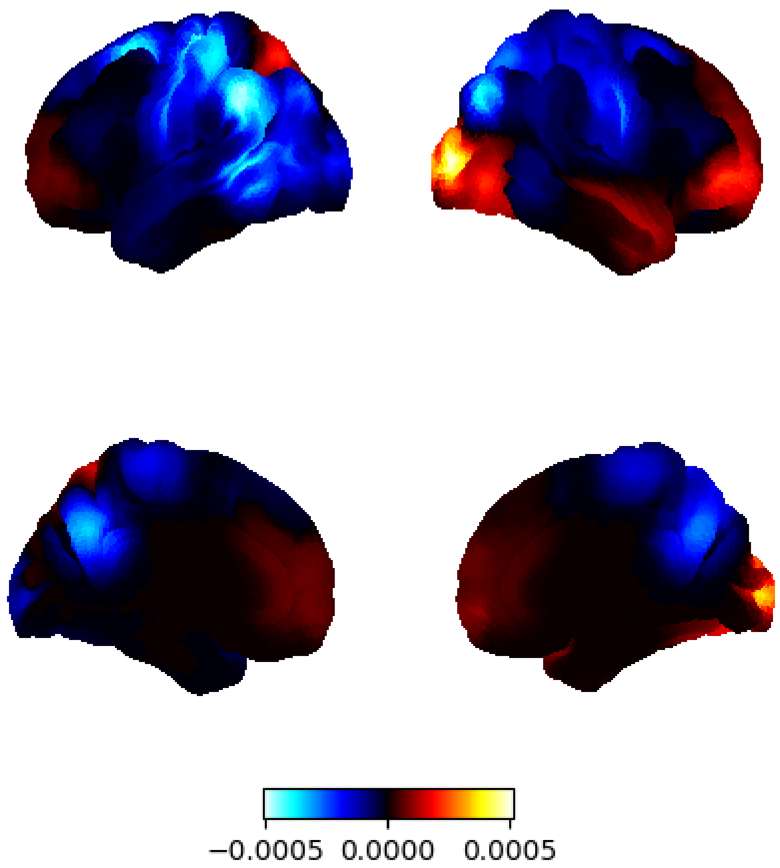



−0.001
0.000
0.001


−2.5
0.0
2.5
1e−9


−0.002
0.000
0.002


−0.0025
0.0000
0.0025



Coherence plots

NNMF

In [299…

```
# Calculate the coherence network for each state by weighting with the spect
c = connectivity.mean_coherence_from_spectra(f, coh, wb_comp)
print(c.shape)

# Average over subjects
mean_c = np.mean(c, axis=0)
print(mean_c.shape)

# Threshold each network and look for the top 3% of connections relative to
thres_mean_c = connectivity.threshold(mean_c, percentile=98, subtract_mean=T
print(thres_mean_c.shape)
```

```
(110, 4, 8, 38, 38)
(4, 8, 38, 38)
(4, 8, 38, 38)
```

In [300…

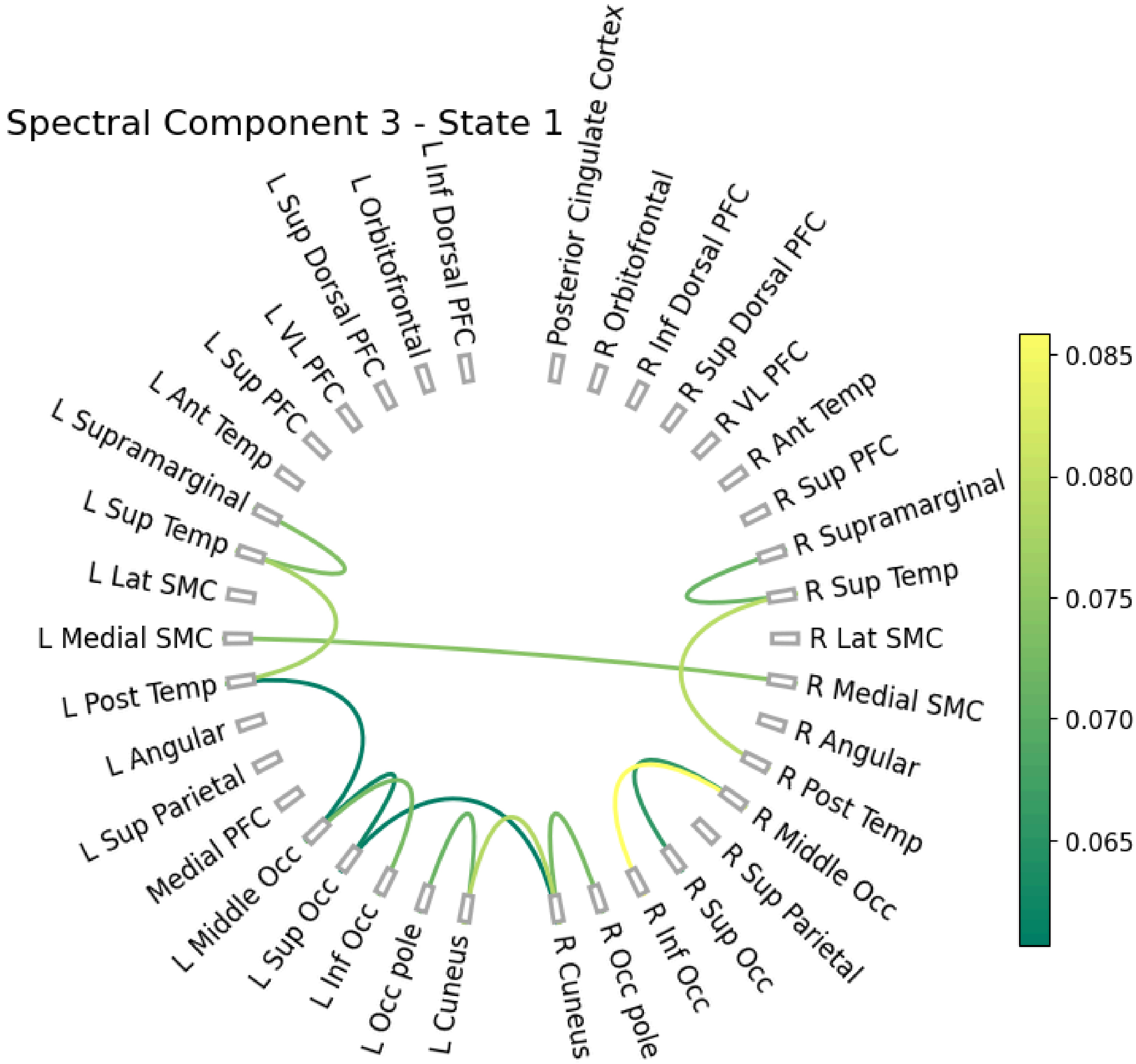
```
sc = 2
os.makedirs(model_name + "/data/Images" + "/Basic_Coherence_NNMF", exist_ok=
connectivity.save(
    thres_mean_c,
    parcellation_file="/home/olivierb/38_parcels.nii",
    component=sc, #1st spectral component
    filename=model_name + "/data/Images/Basic_Coherence_NNMF/coh_Spectral_Co
)
```

```
Saving images: 100%|██████████| 8/8 [00:10<00:00,  1.35s/it]
```

Thresholded 2%

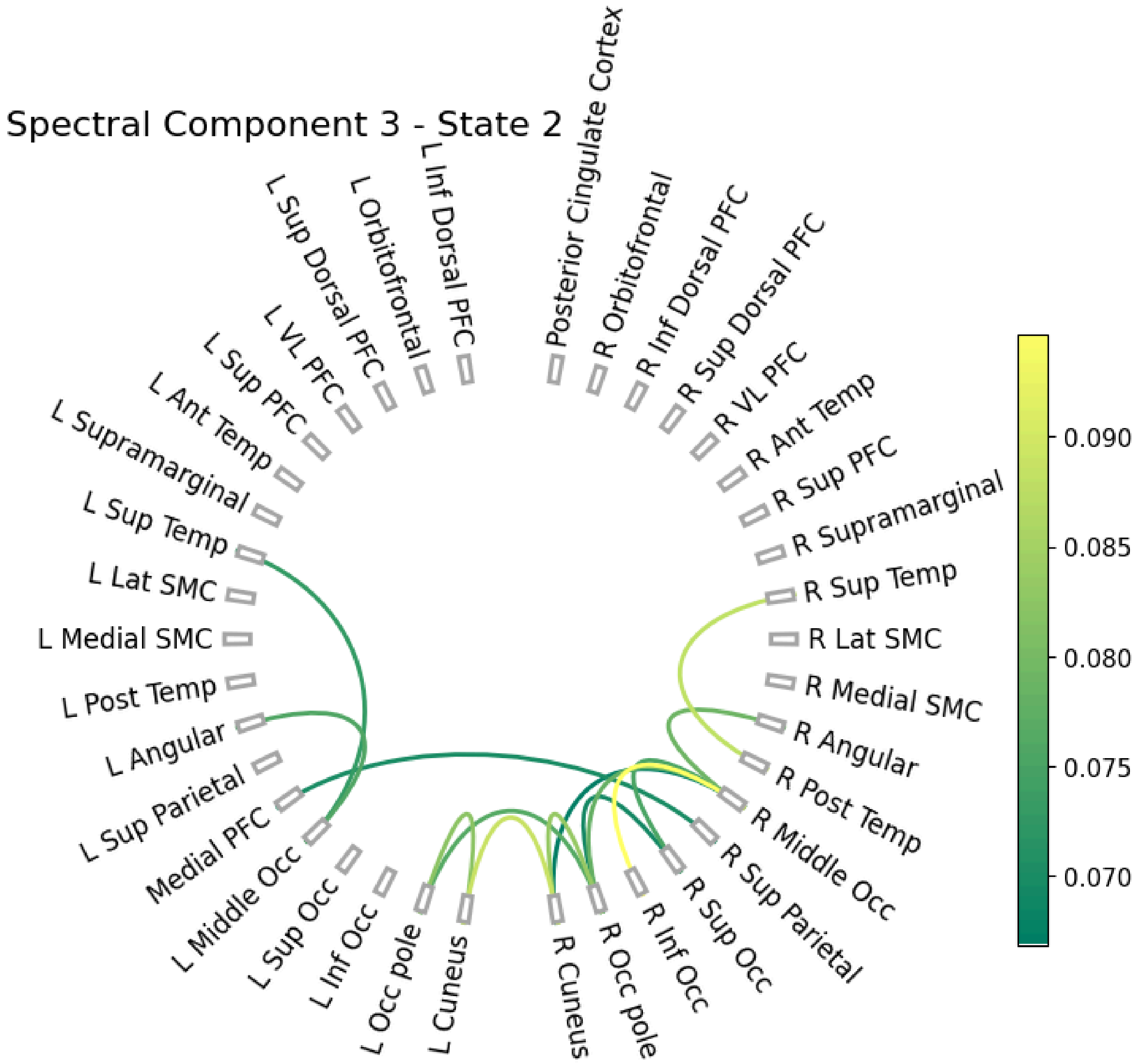
In [278…

```
connectivity_6states_SC3 = thres_mean_c[2]
connectivity_6states_SC3_S1 = connectivity_6states_SC3[0]

sc=2
title = 'Spectral Component 3 - State 1
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```



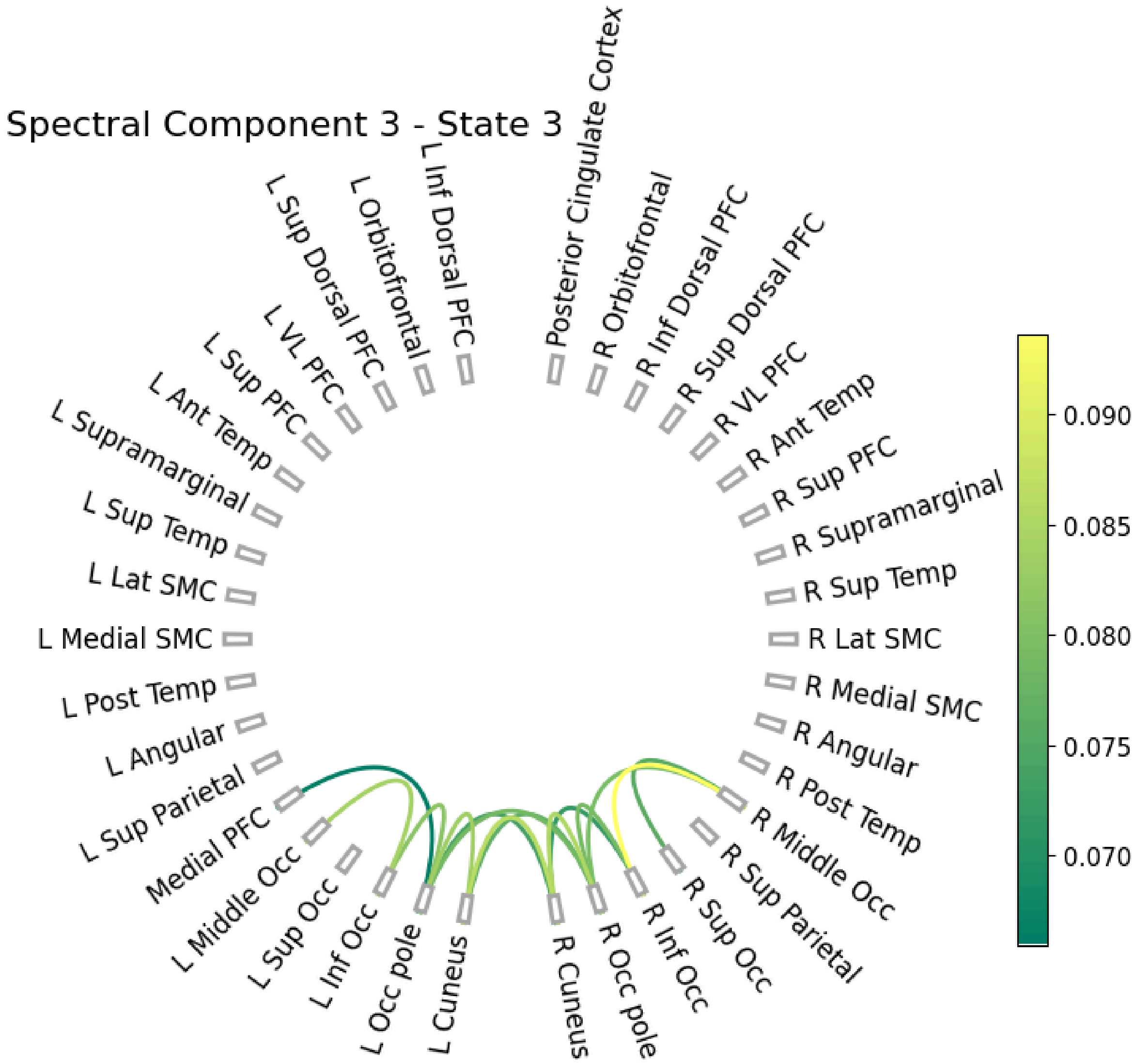
In [279…

```
connectivity_6states_SC3_S2 = connectivity_6states_SC3[1]

sc=2
title = 'Spectral Component 3 - State 2
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```



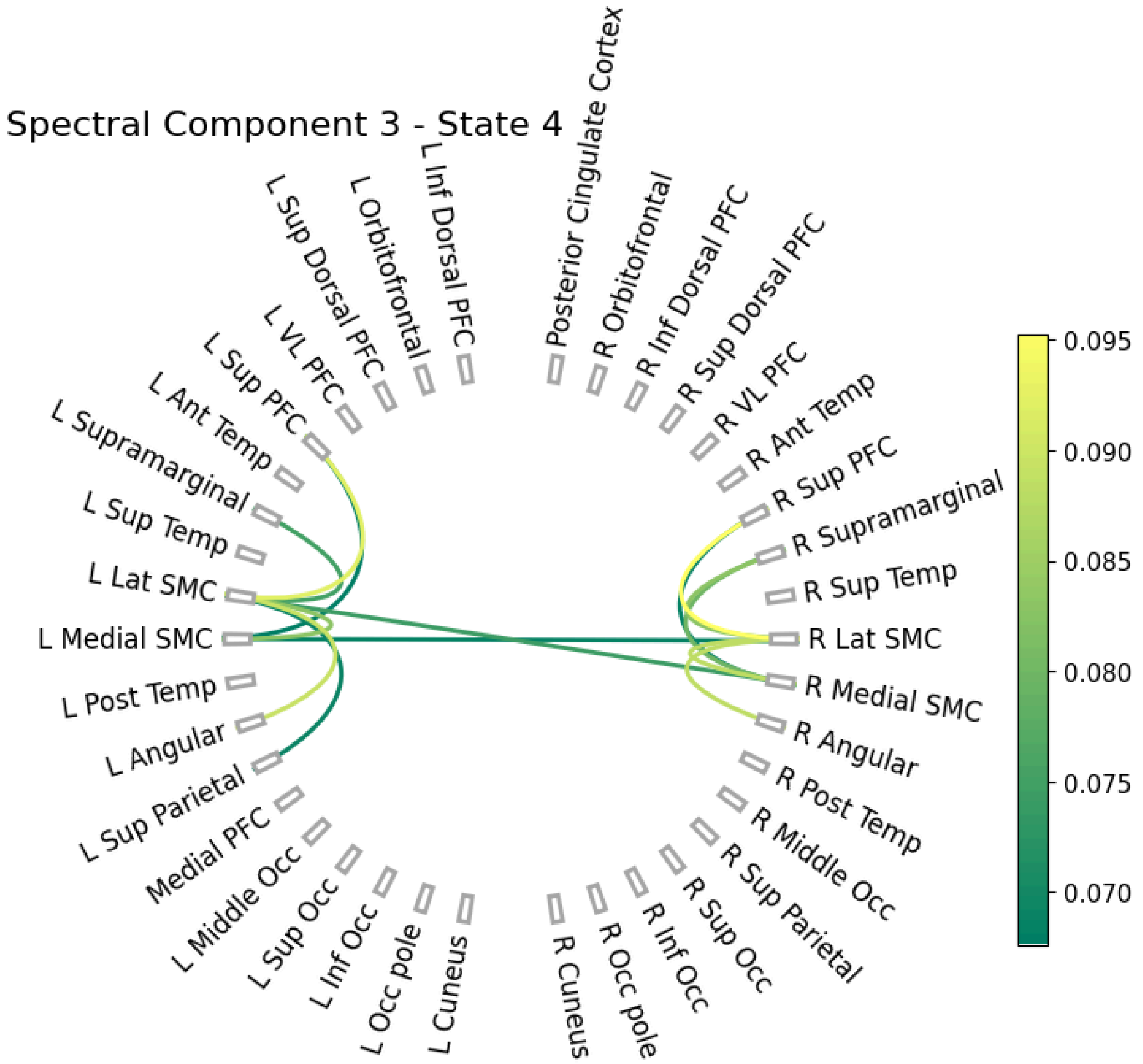
In [280…

```
connectivity_6states_SC3_S3 = connectivity_6states_SC3[2]

sc=2
title = 'Spectral Component 3 - State 3
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```



In [281…

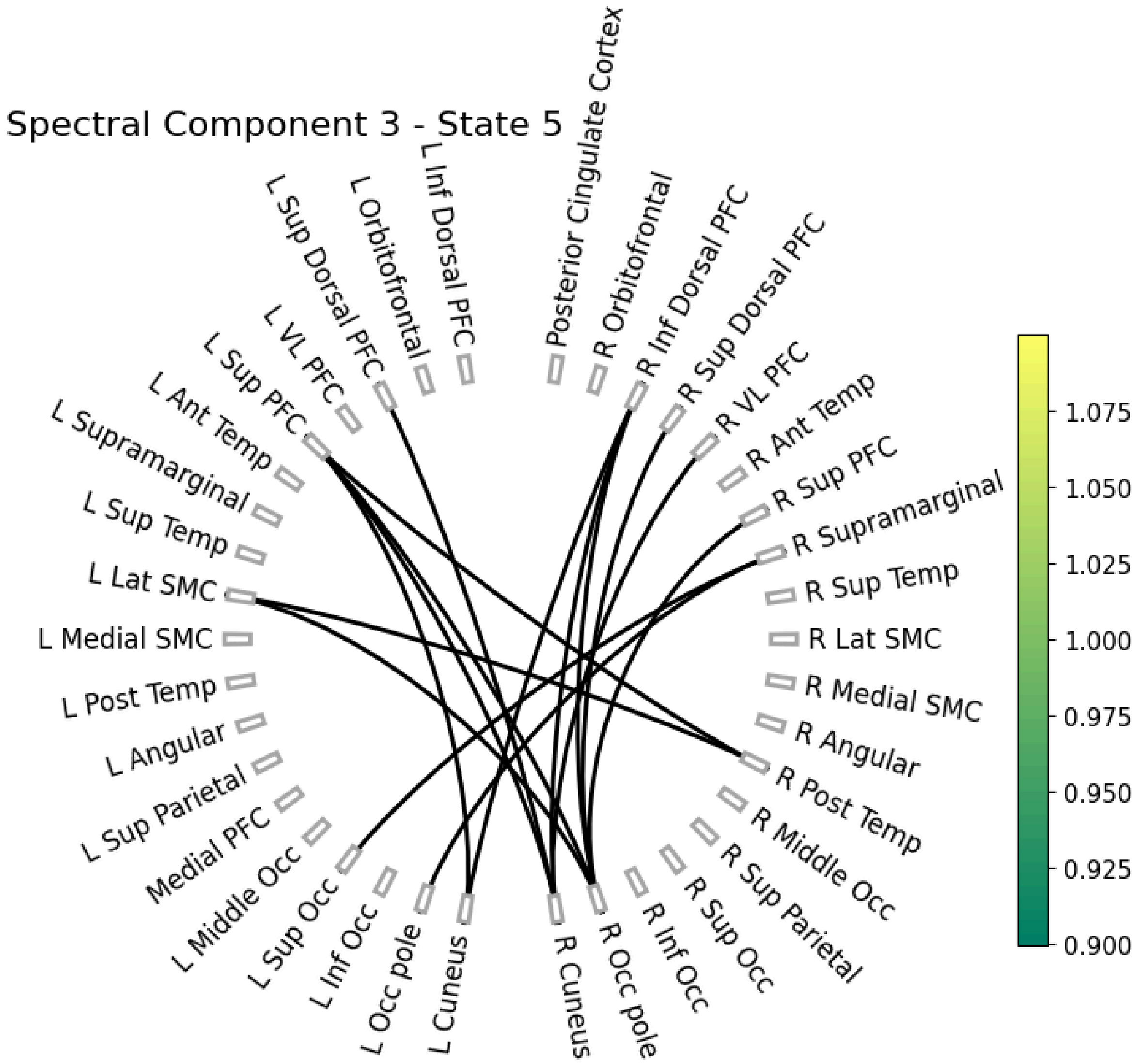
```
connectivity_6states_SC3_S4 = connectivity_6states_SC3[3]

sc=2
title = 'Spectral Component 3 - State 4
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```



In [282…

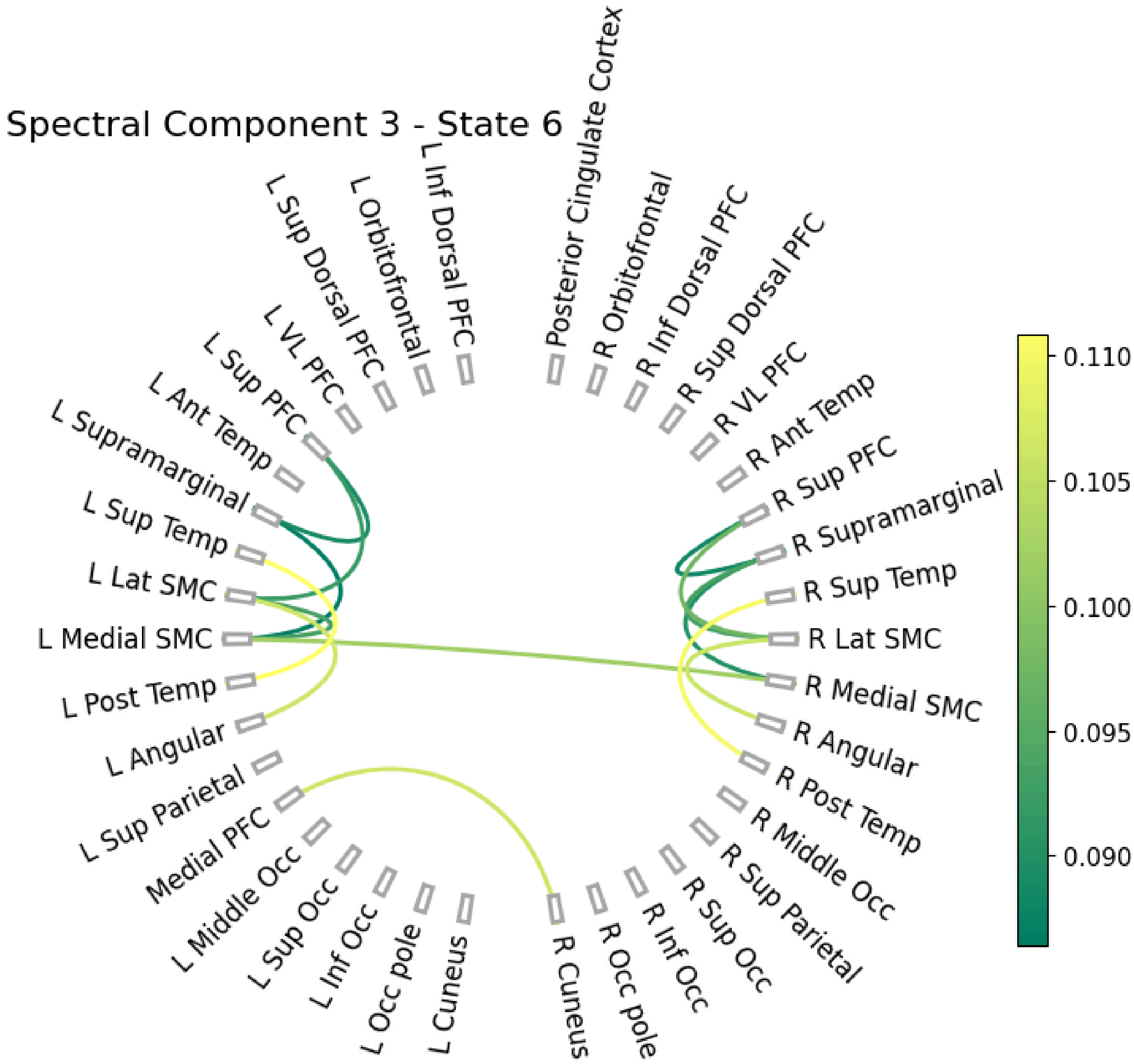
```
connectivity_6states_SC3_S5 = connectivity_6states_SC3[4]

sc=2
title = 'Spectral Component 3 - State 5
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```

```
/home/olivierb/.local/lib/python3.9/site-packages/mne/viz/circle.py:289:
RuntimeWarning: invalid value encountered in divide
  con_val_scaled = (con - vmin) / vrange
```



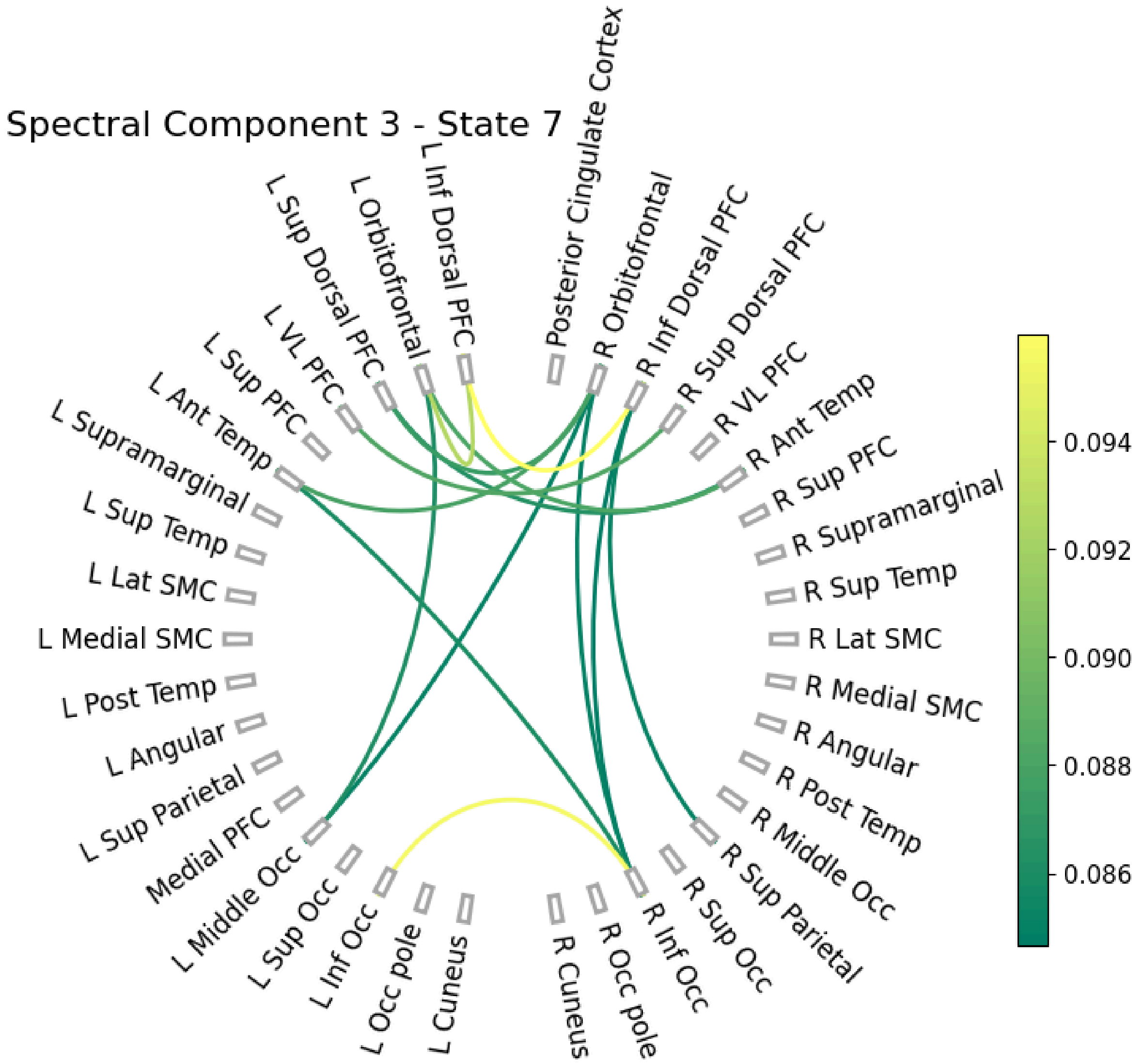
In [283…

```
connectivity_6states_SC3_S6 = connectivity_6states_SC3[5]

sc=2
title = 'Spectral Component 3 - State 6
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```



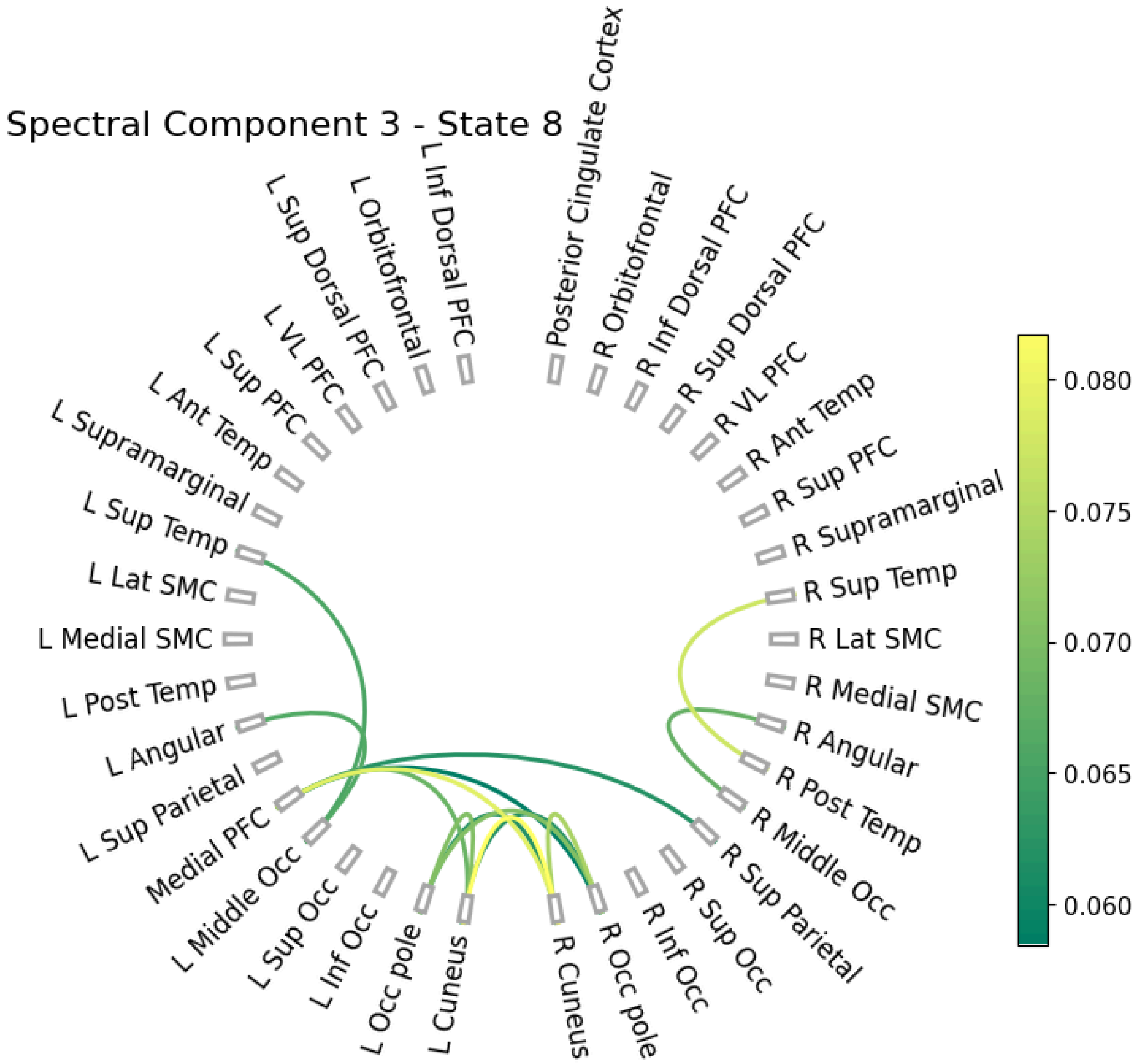
In [284…

```
connectivity_6states_SC3_S7 = connectivity_6states_SC3[6]

sc=2
title = 'Spectral Component 3 - State 7
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```



In [285…

```
connectivity_6states_SC3_S8 = connectivity_6states_SC3[7]

sc=2
title = 'Spectral Component 3 - State 8
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```



Data-driven thresholding: Gaussian Mixture Model (GMM)

In [286…

```
mean_c = mean_c[:][:,np.array([True, True, True, True, False, True, True, Tr
print(np.shape(mean_c))
```

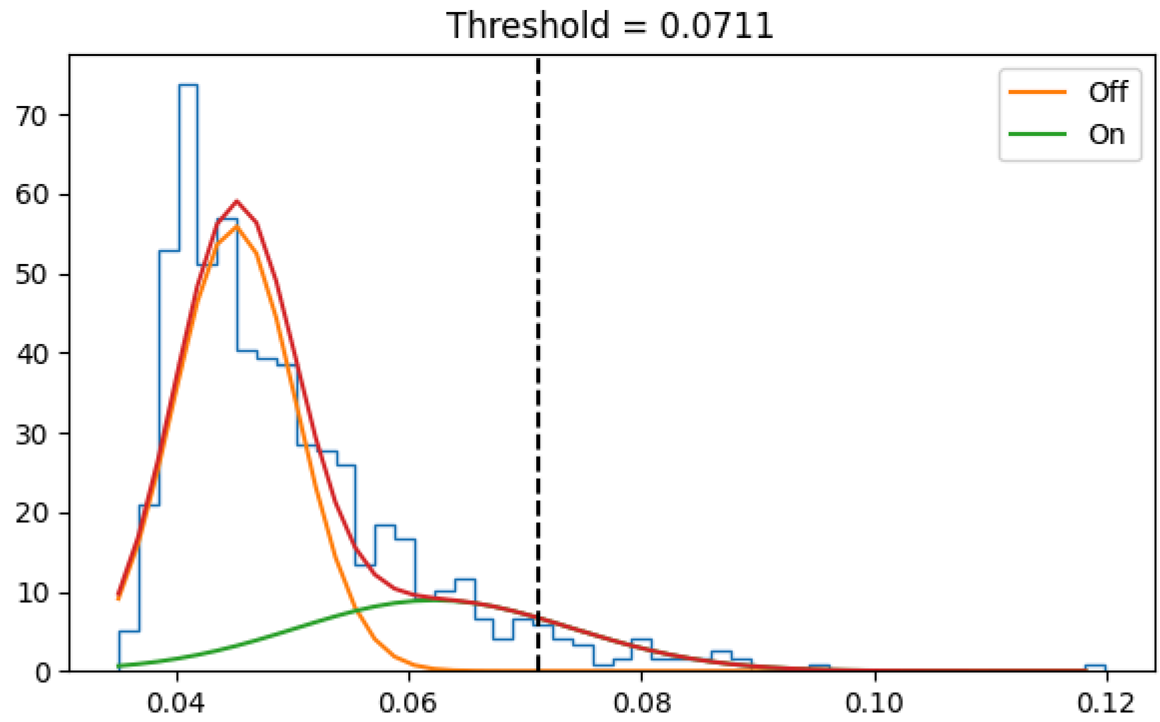
```
(4, 7, 38, 38)
```

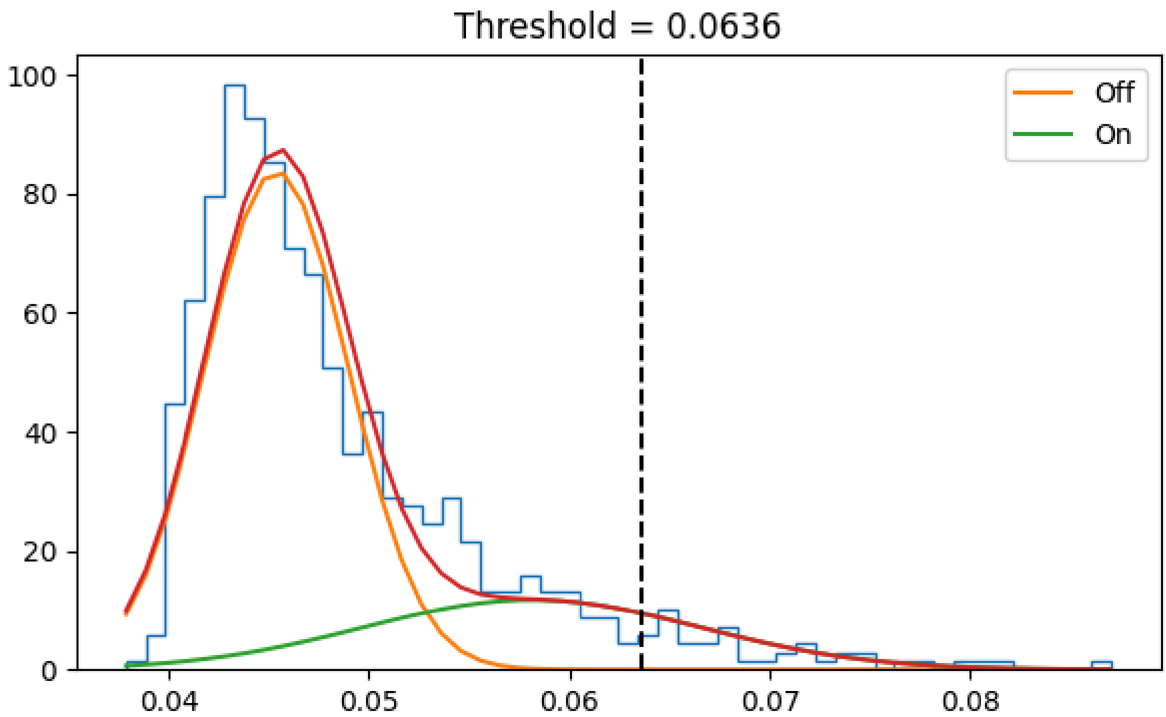
In [287…

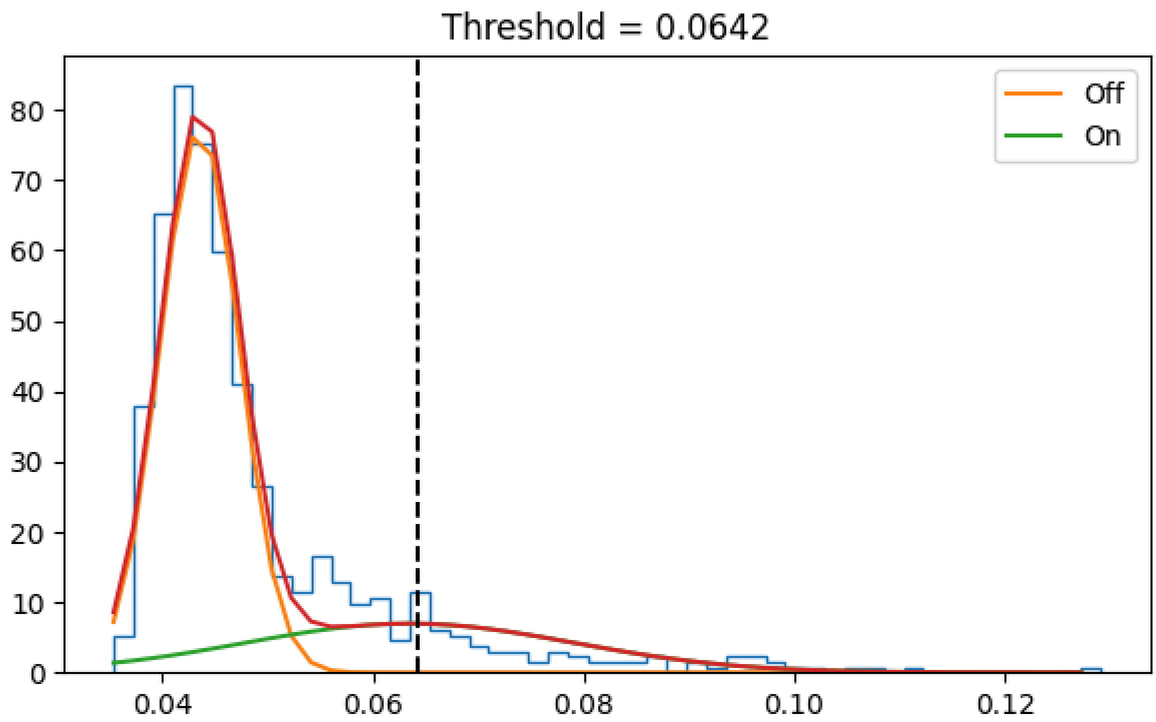
```
## This only needs to be ran once (it does the GMM data-driven thresholding

sc = 2

# Threshold each network using a GMM
thres_mean_c = connectivity.gmm_threshold(
    mean_c,
    p_value=0.05,
    keep_positive_only=True,
    #subtract_mean=True,
    show=True,
)
print(thres_mean_c.shape)

os.makedirs(model_name + "/data/Images" + "/Basic_Coherence_GMM", exist_ok=T
```

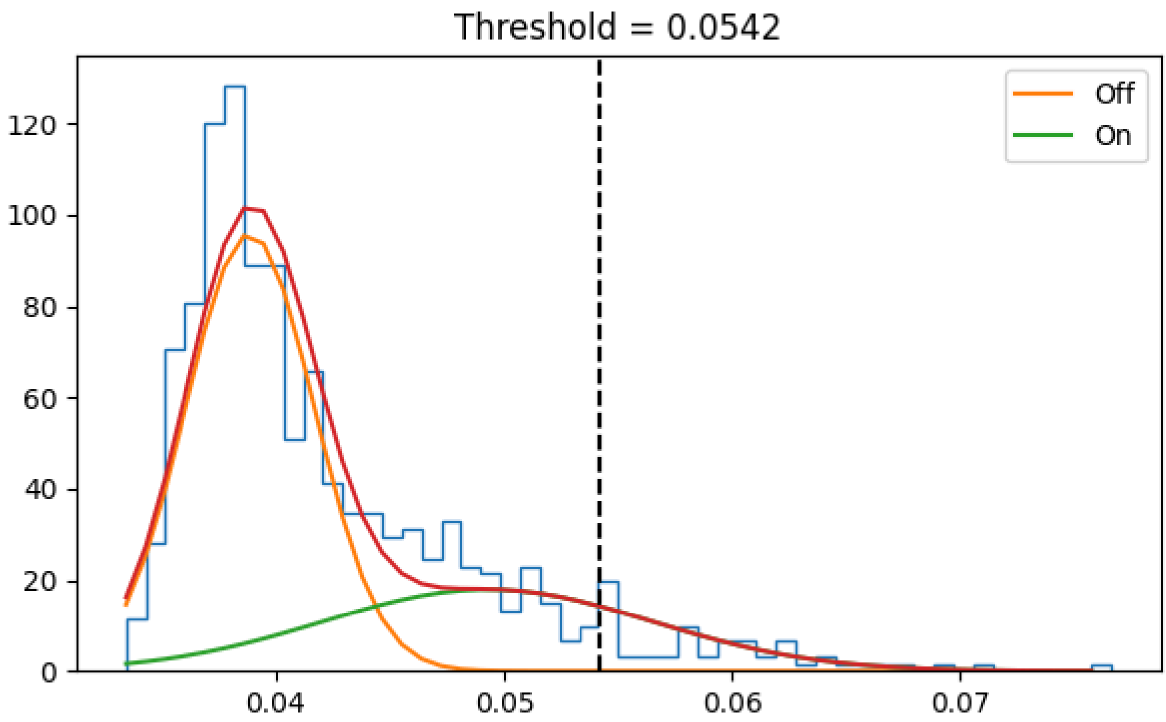
```python
# Plot
connectivity.save(
    thres_mean_c,
    parcellation_file="/home/olivierb/38_parcels.nii",
    component=sc,
    filename=model_name + "/data/Images/Basic_Coherence_GMM/coh_Spectral_Com
)
```

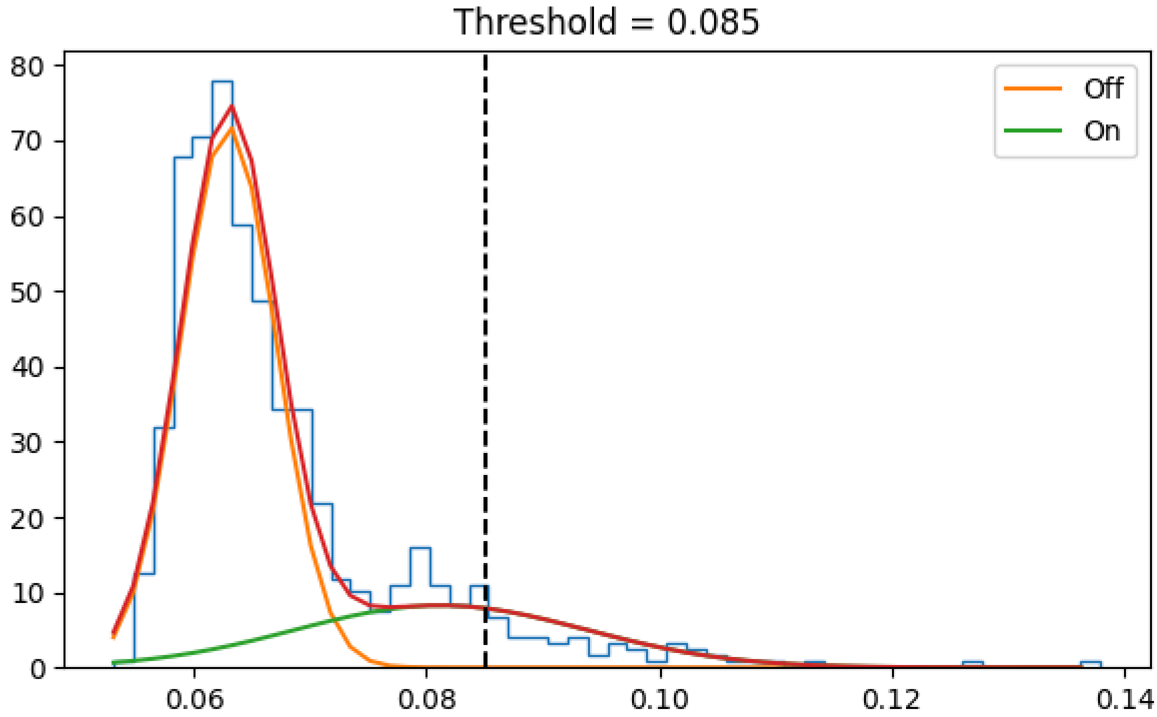
```
/home/olivierb/osl-dynamics/osl_dynamics/utils/plotting.py:72: RuntimeWarni
ng: More than 20 figures have been opened. Figures created through the pypl
ot interface (`matplotlib.pyplot.figure`) are retained until explicitly clo
sed and may consume too much memory. (To control this warning, see the rcPa
ram `figure.max_open_warning`). Consider using `matplotlib.pyplot.close()`.
  fig, ax = plt.subplots(*args, **kwargs)
(4, 7, 38, 38)
Saving images: 100%|██████████| 7/7 [00:10<00:00,  1.53s/it]
```

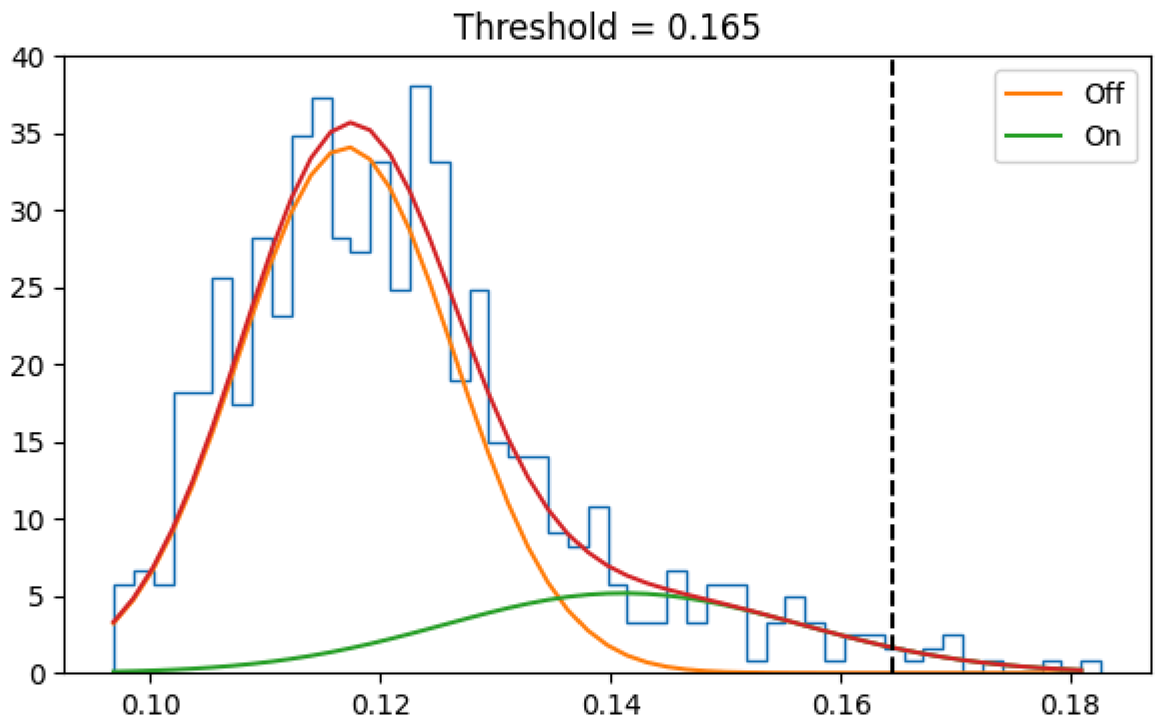


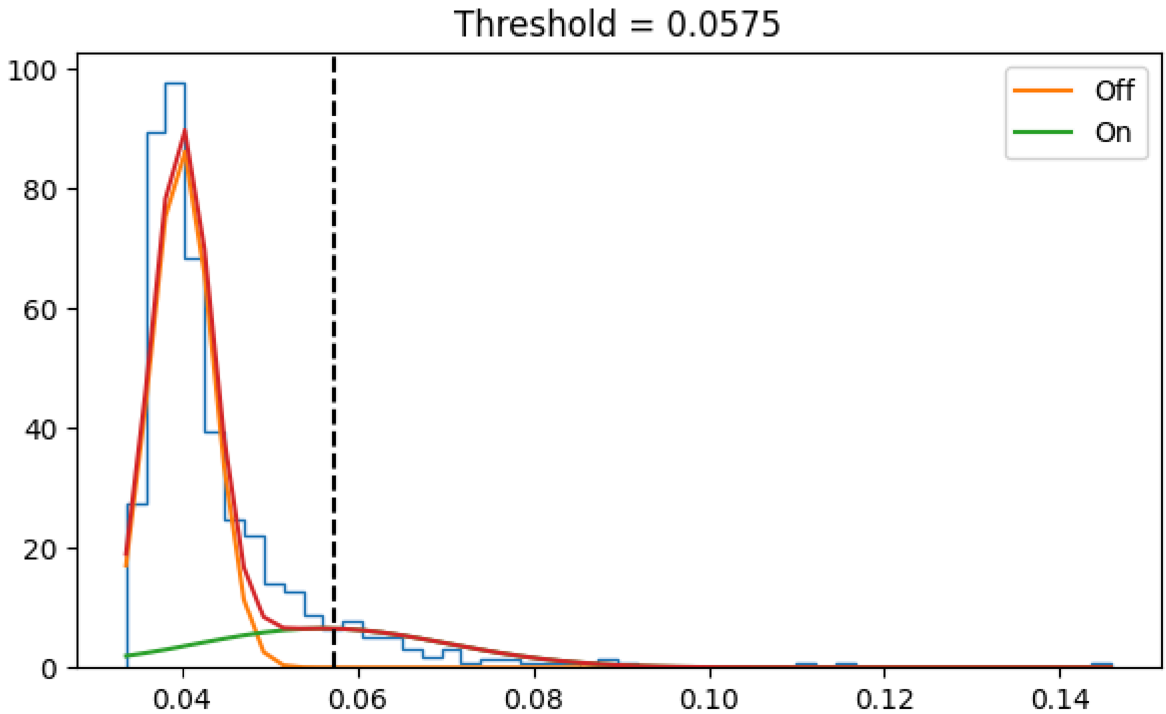


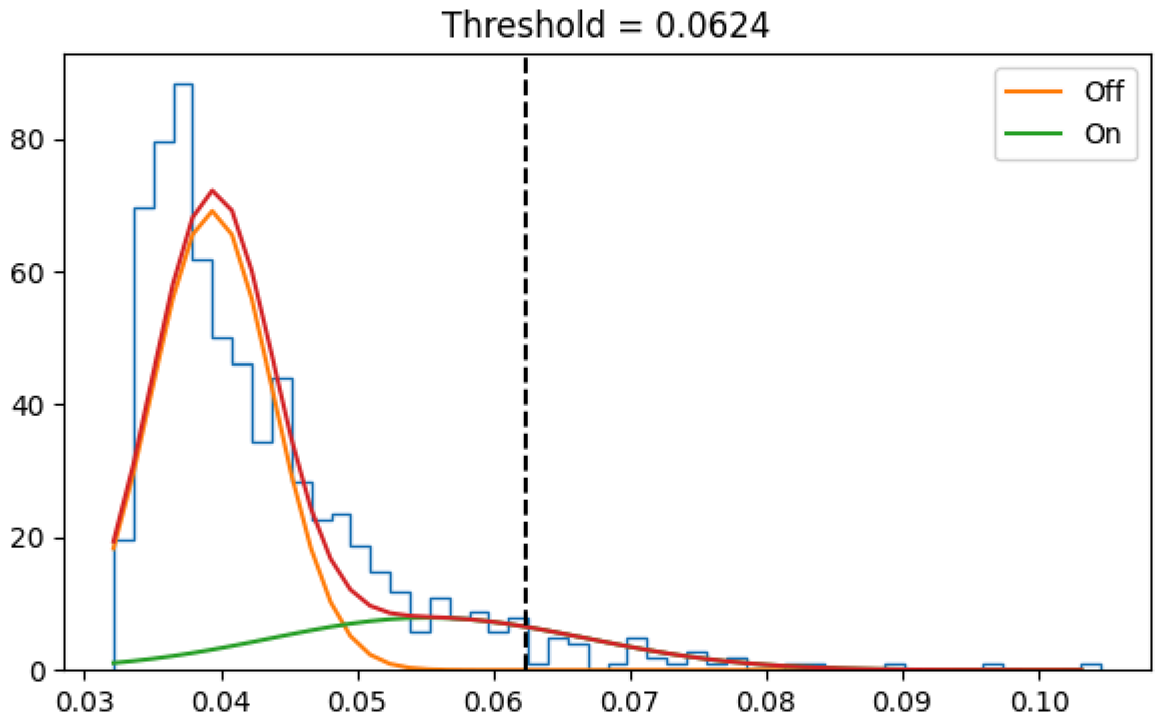

Threshold = 0.0642
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.06
0.08
0.10
0.12

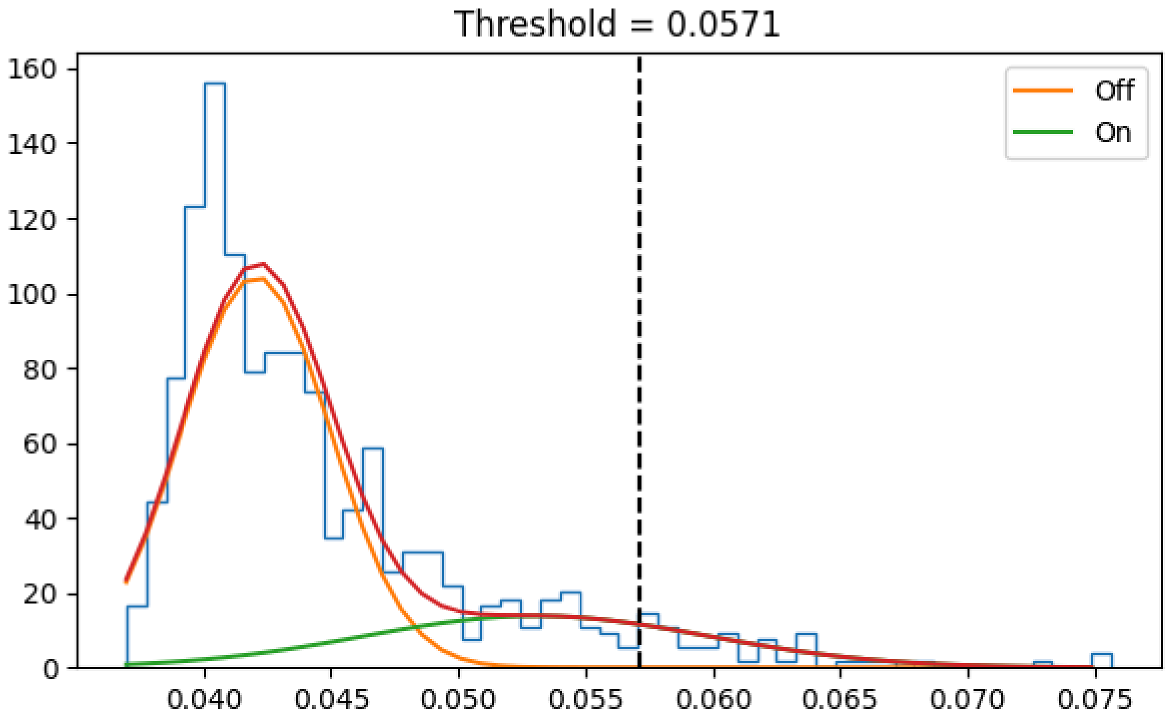

Threshold = 0.0542
Off
On
0
20
40
60
80
100
120
0.04
0.05
0.06
0.07

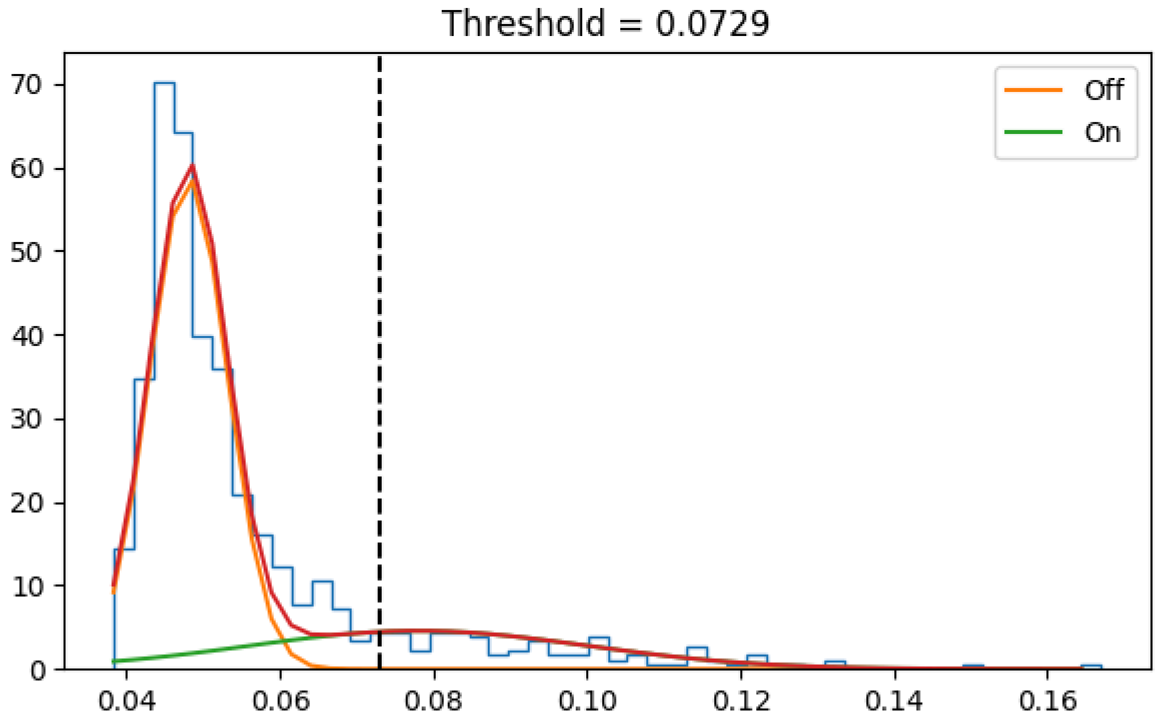

Threshold = 0.085
Off
On
0
10
20
30
40
50
60
70
80
0.06
0.08
0.10
0.12
0.14

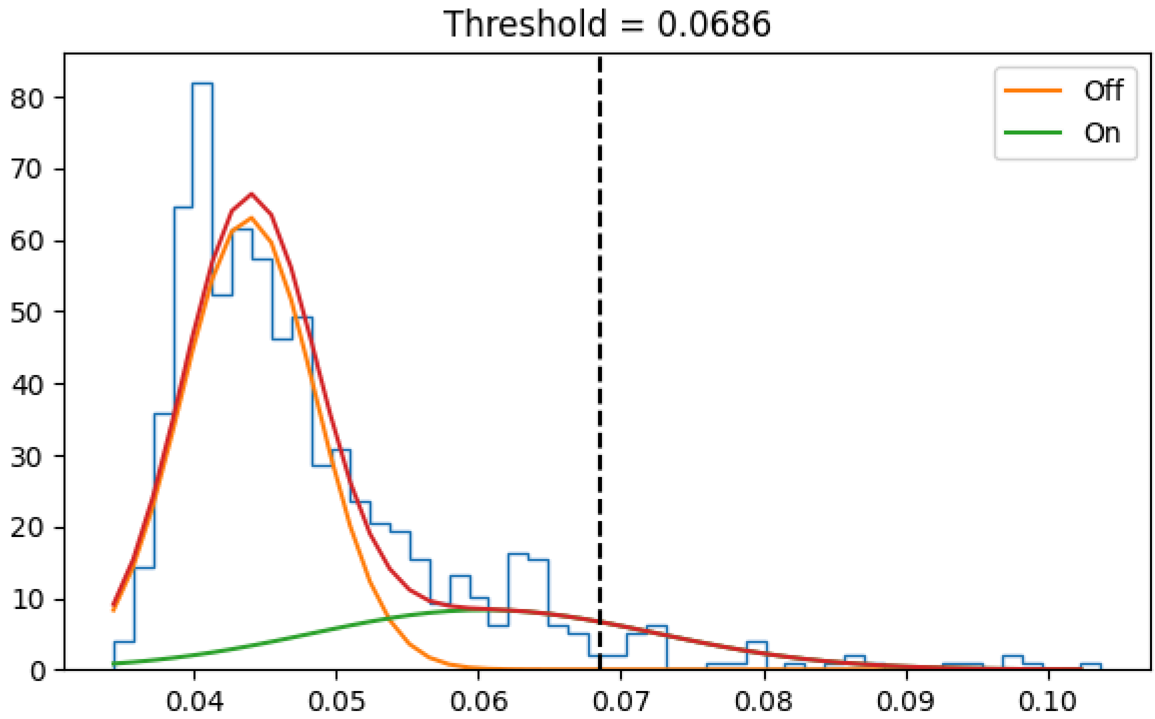

Threshold = 0.165
Off
On
0
5
10
15
20
25
30
35
40
0.10
0.12
0.14
0.16
0.18

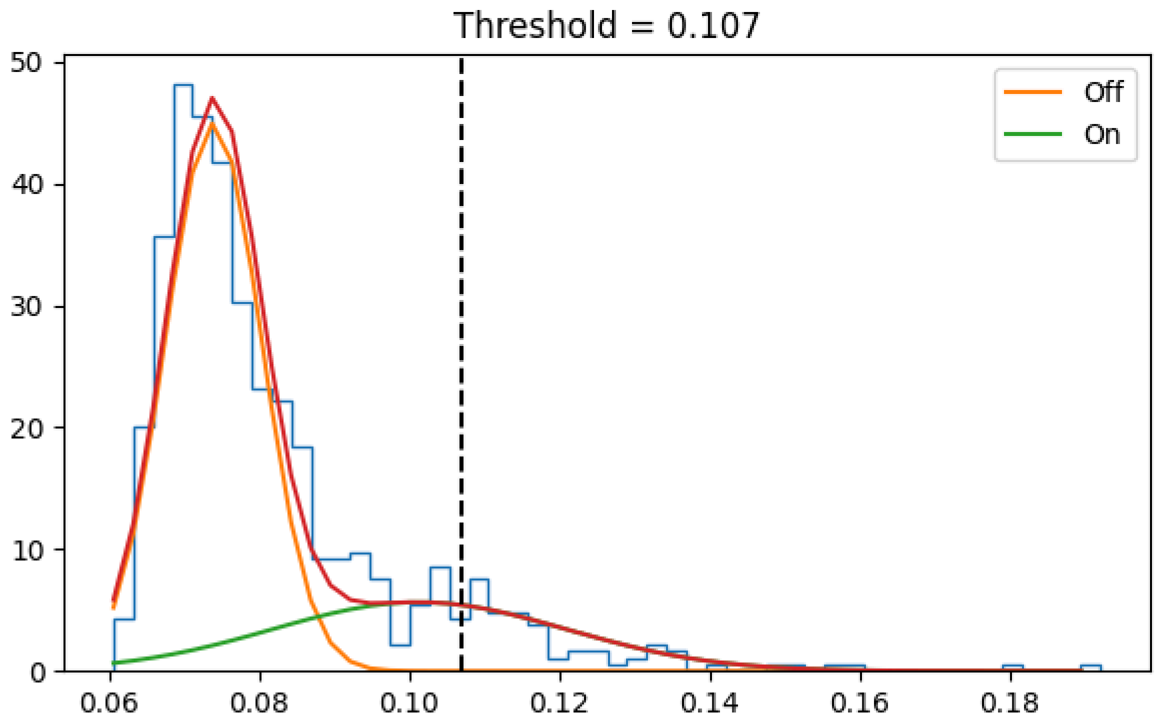

Threshold = 0.0575
Off
On
100
80
60
40
20
0
0.04
0.06
0.08
0.10
0.12
0.14

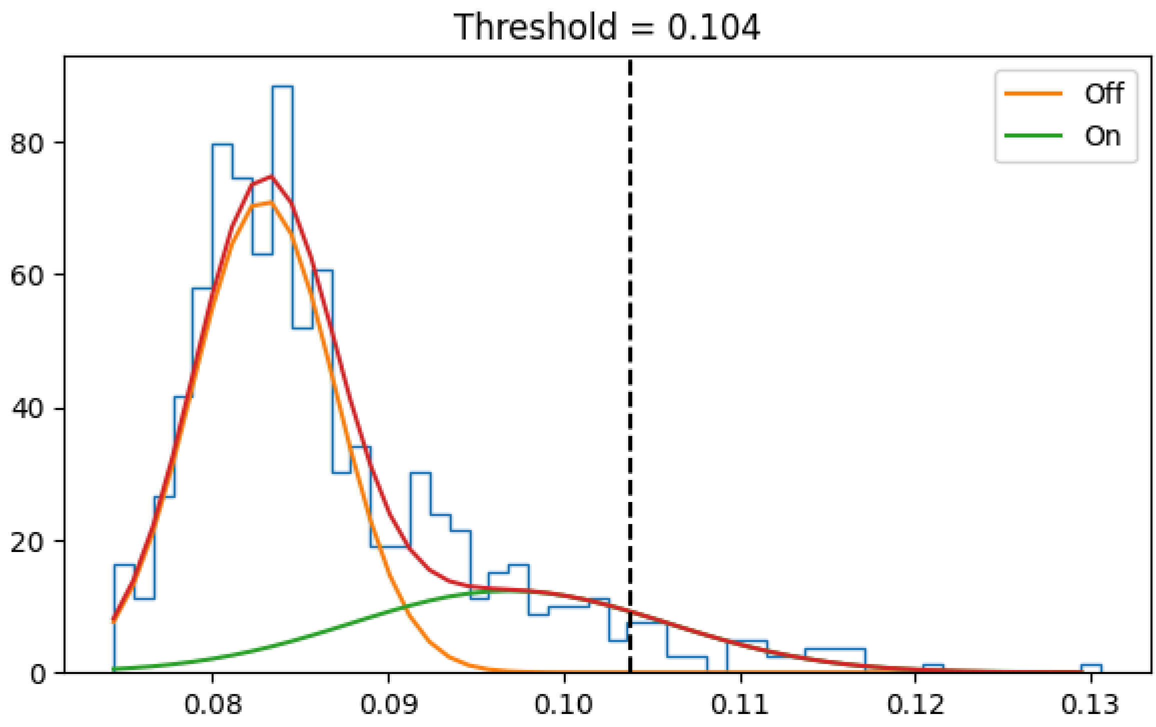

Threshold = 0.0624
Off
On
80
60
40
20
0
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10

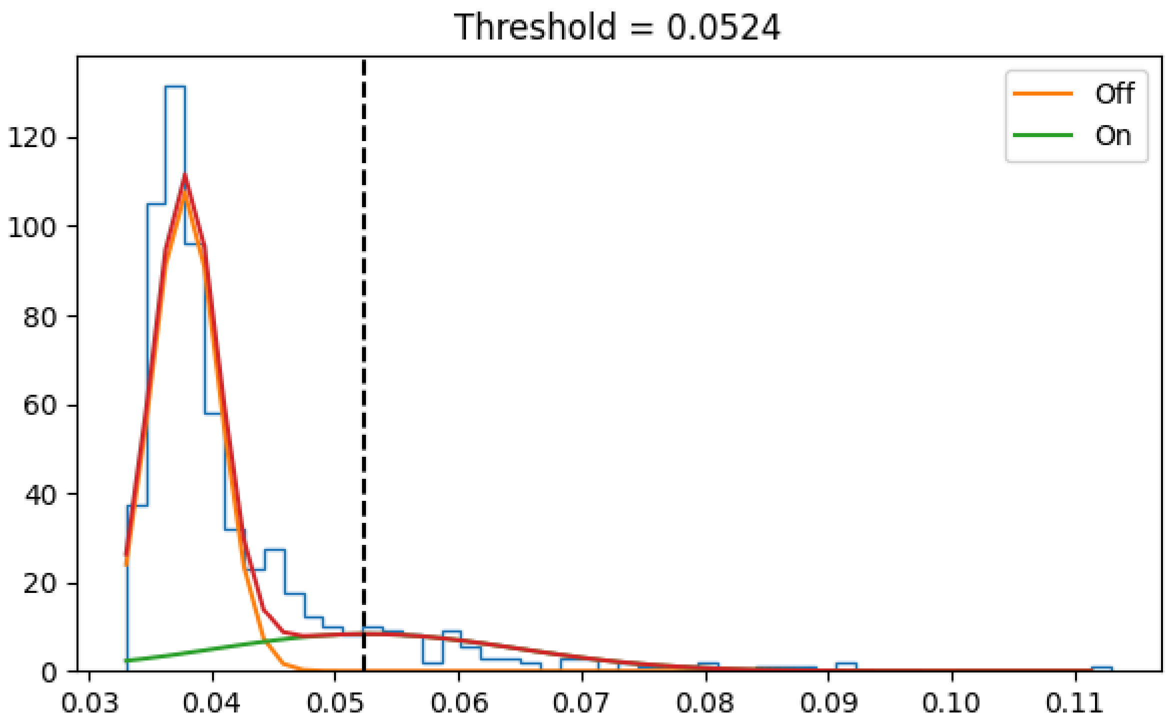

Threshold = 0.0571
Off
On
160
140
120
100
80
60
40
20
0
0.040
0.045
0.050
0.055
0.060
0.065
0.070
0.075

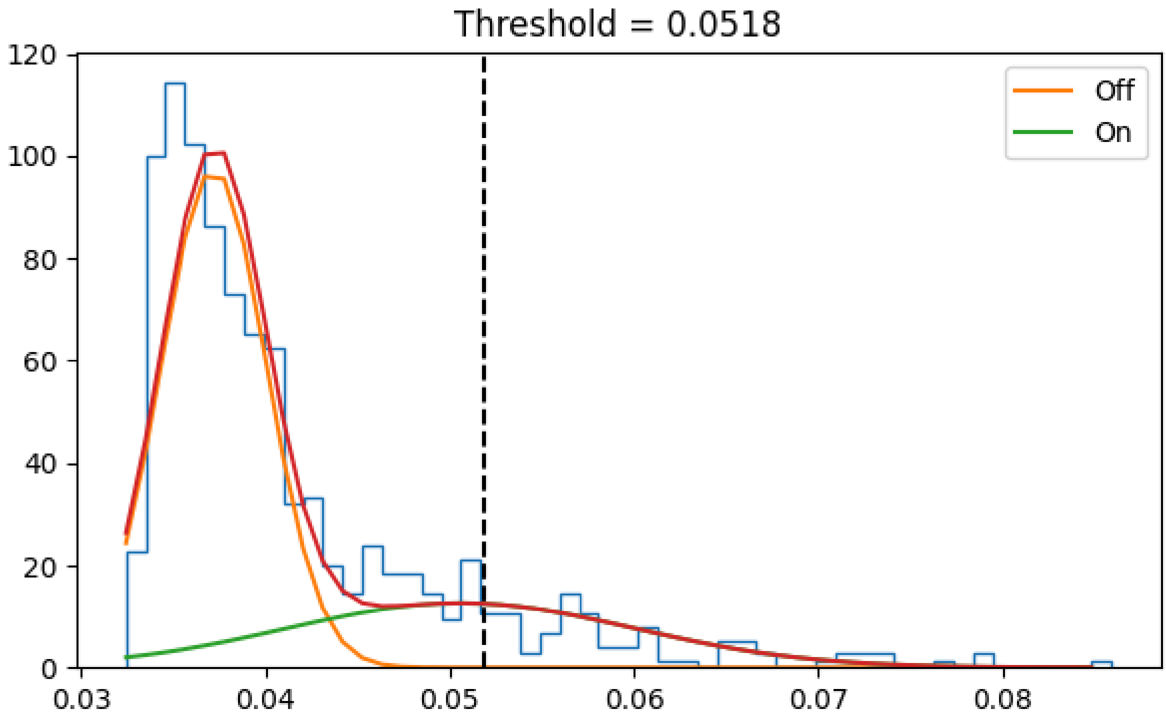

Threshold = 0.0729
Off
On
70
60
50
40
30
20
10
0
0.04
0.06
0.08
0.10
0.12
0.14
0.16


Threshold = 0.0686
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.05
0.06
0.07
0.08
0.09
0.10

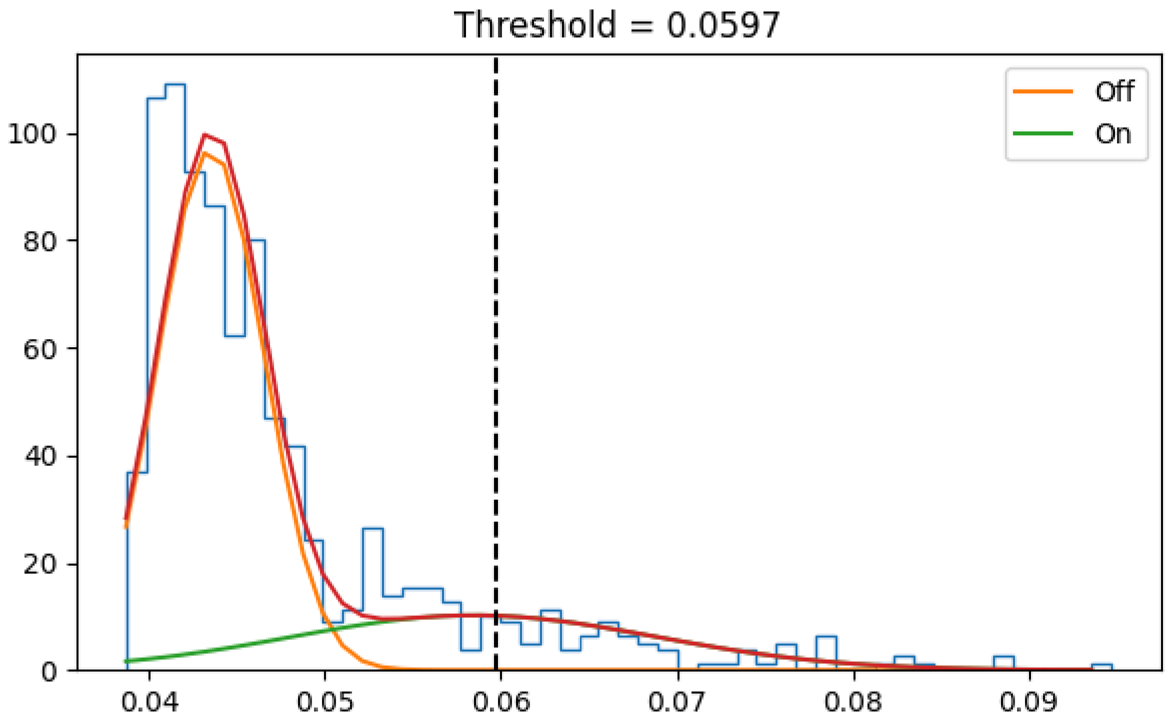

Threshold = 0.107
Off
On
0
10
20
30
40
50
0.06
0.08
0.10
0.12
0.14
0.16
0.18


Threshold = 0.104
Off
On
0
20
40
60
80
0.08
0.09
0.10
0.11
0.12
0.13

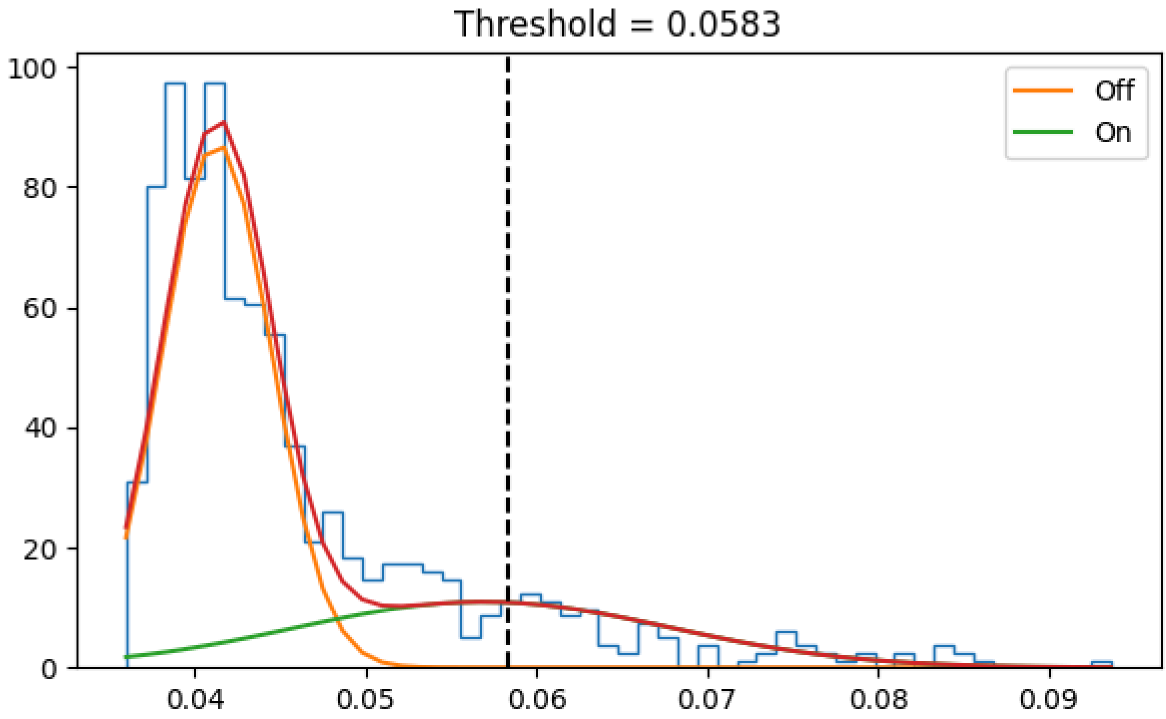

Threshold = 0.0524
Off
On
0
20
40
60
80
100
120
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10
0.11

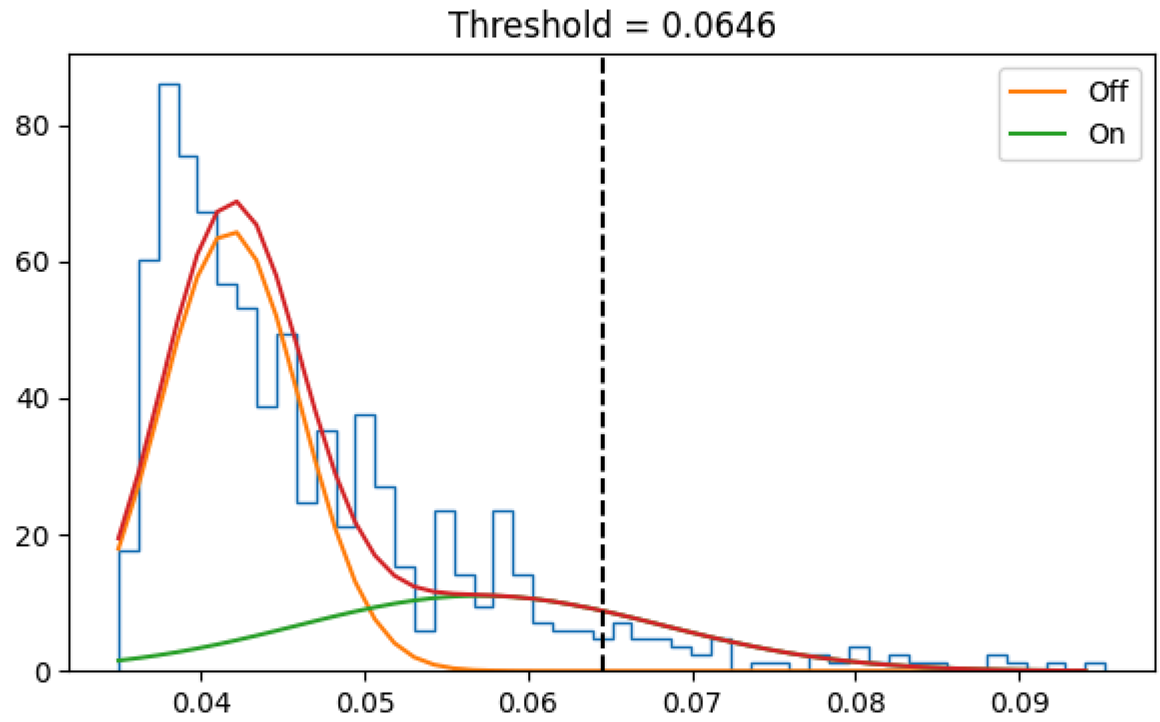


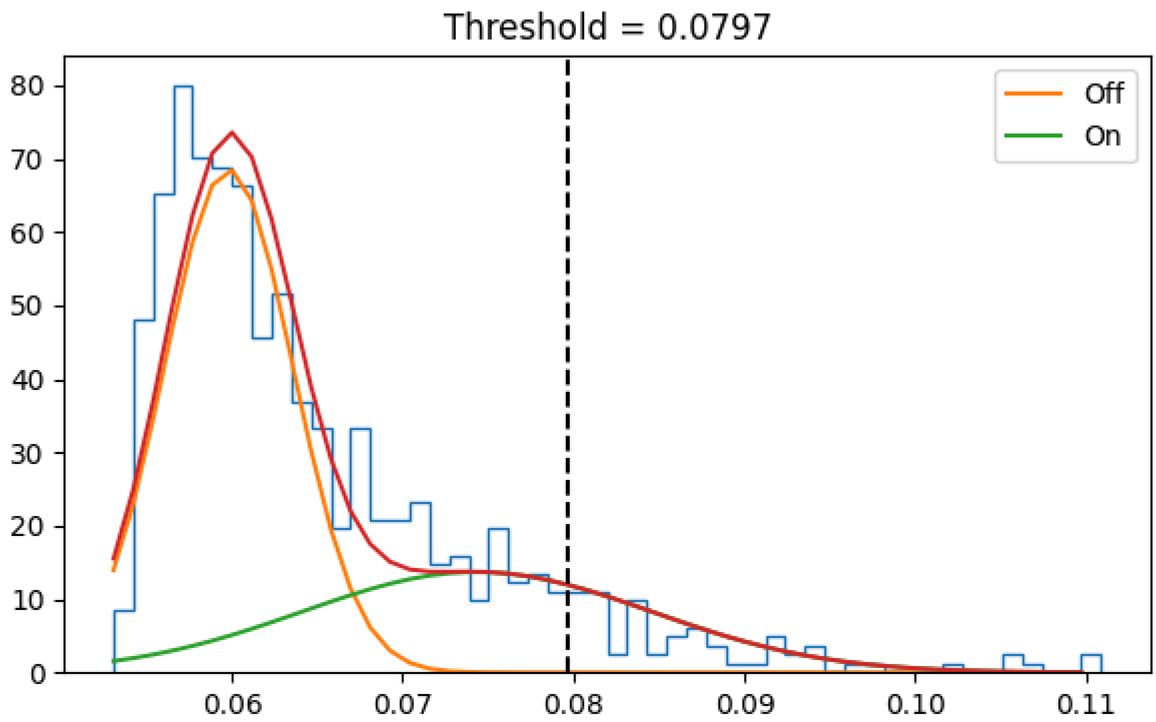
Threshold = 0.0518
Off
On
0
20
40
60
80
100
120
0.03
0.04
0.05
0.06
0.07
0.08

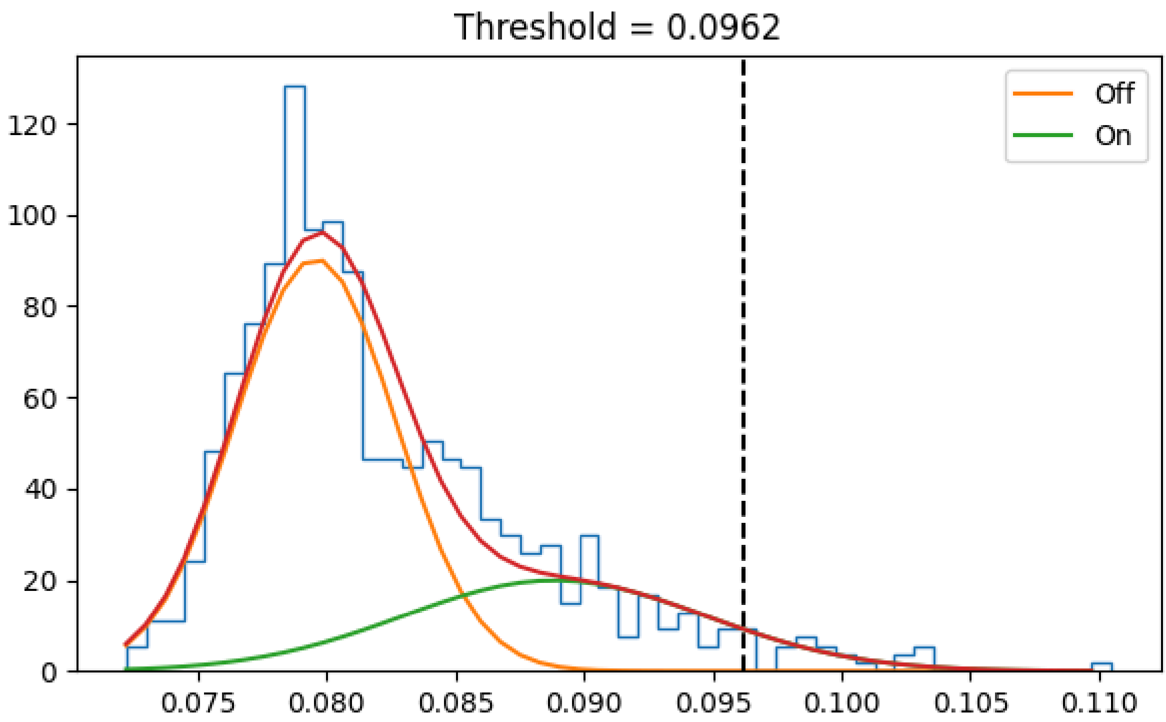


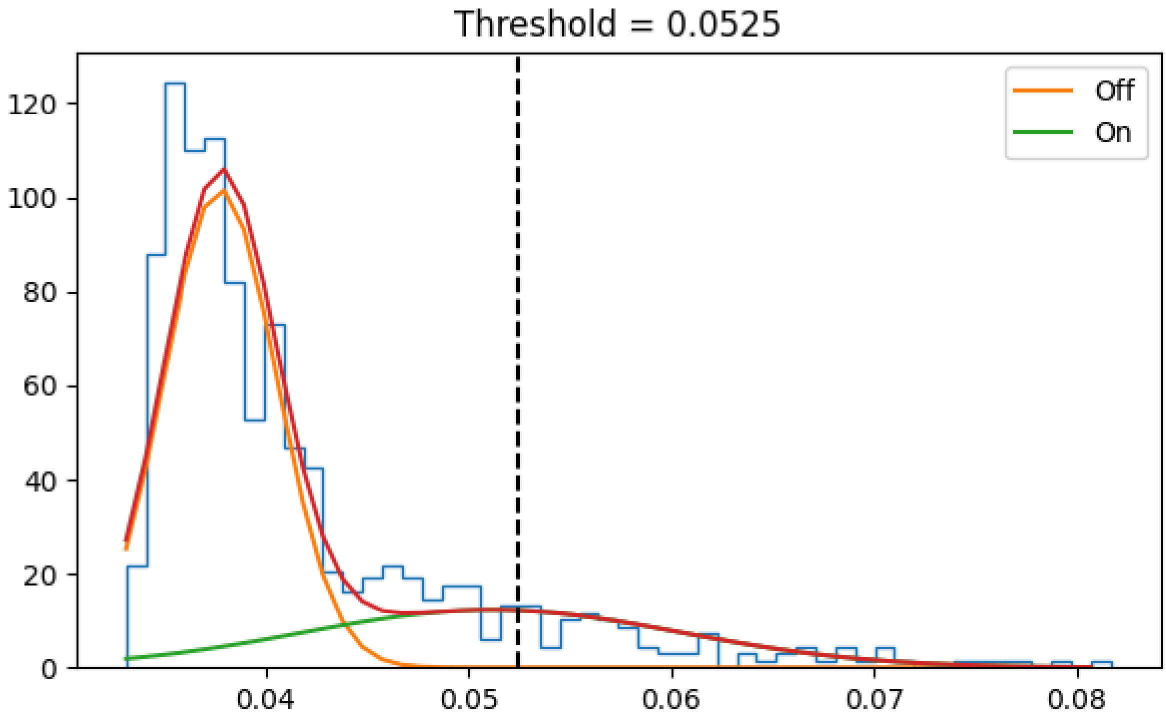
Threshold = 0.0597
Off
On
0
20
40
60
80
100
0.04
0.05
0.06
0.07
0.08
0.09

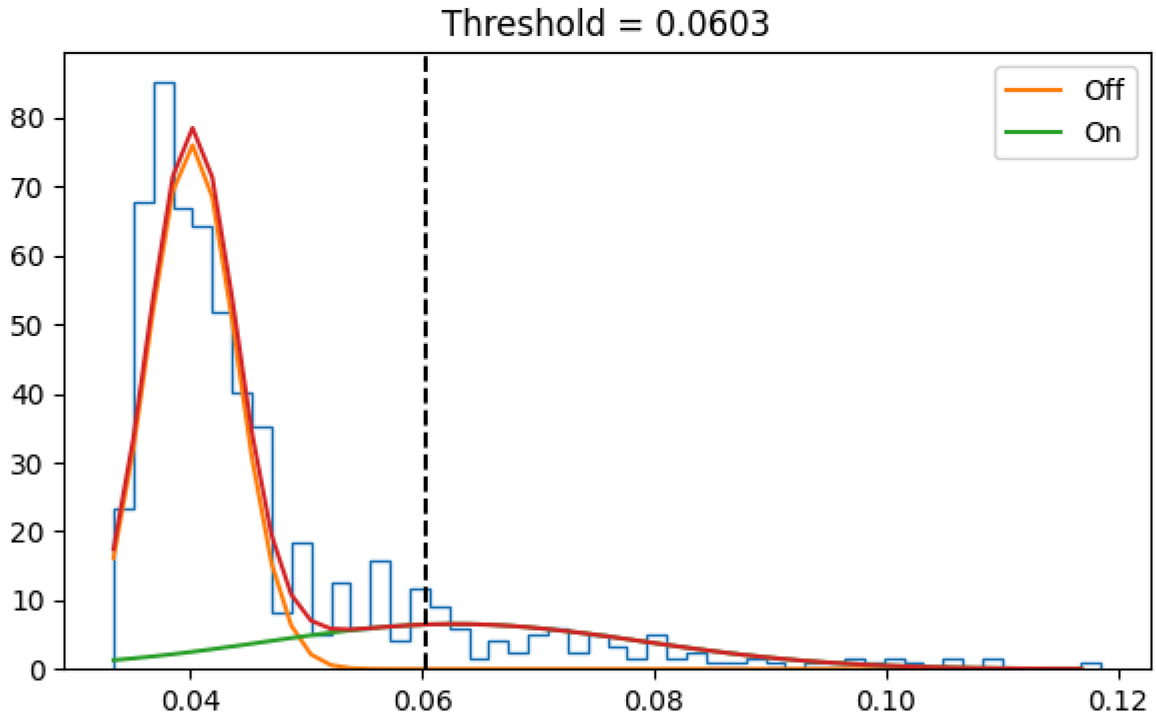

Threshold = 0.0583
Off
On
100
80
60
40
20
0
0.04
0.05
0.06
0.07
0.08
0.09

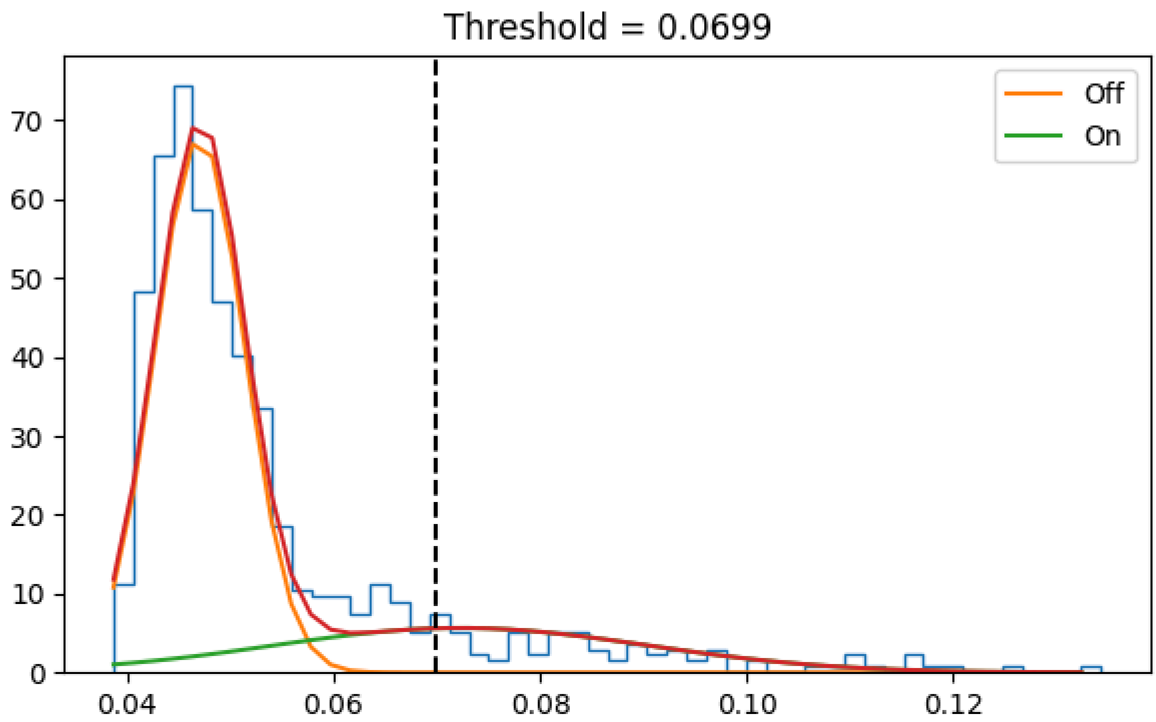

Threshold = 0.0646
Off
On
80
60
40
20
0
0.04
0.05
0.06
0.07
0.08
0.09

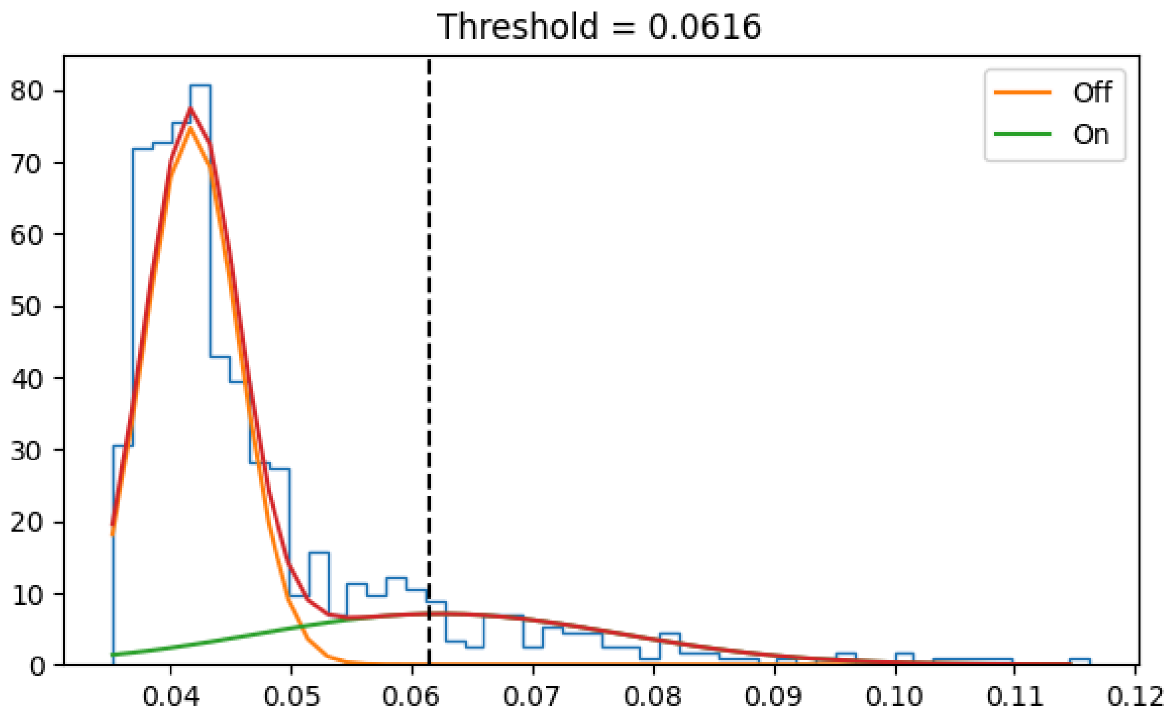

Threshold = 0.0797
Off
On
80
70
60
50
40
30
20
10
0
0.06
0.07
0.08
0.09
0.10
0.11

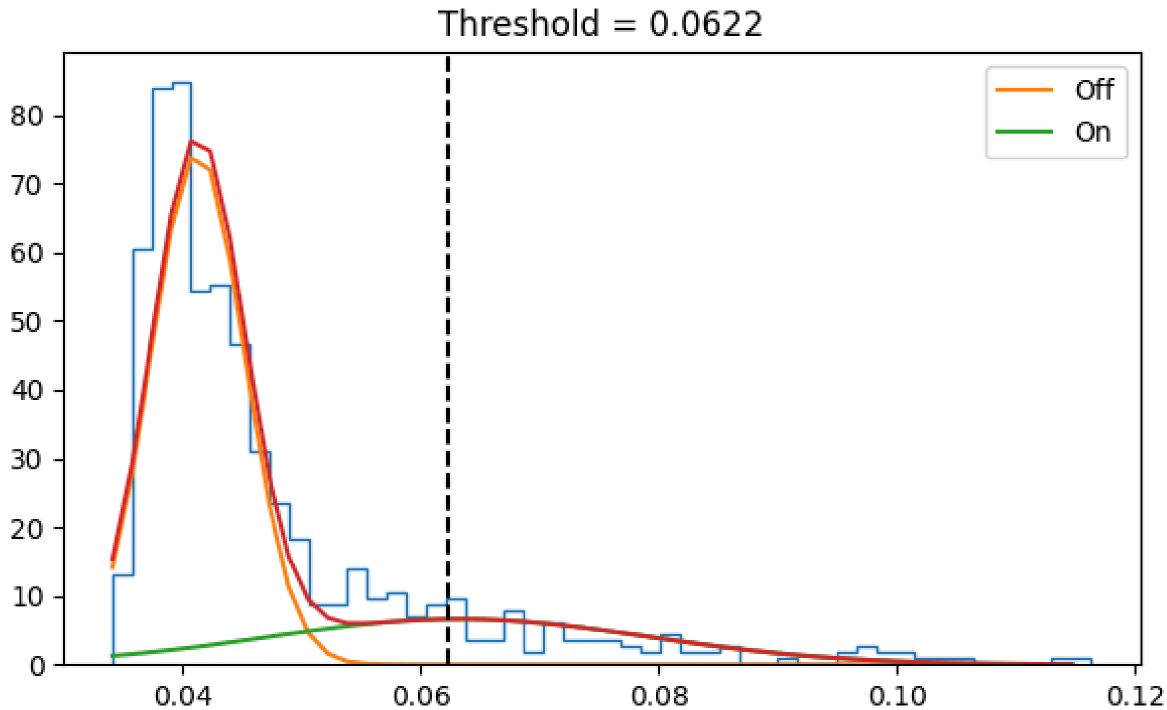

Threshold = 0.0962
Off
On
120
100
80
60
40
20
0
0.075
0.080
0.085
0.090
0.095
0.100
0.105
0.110

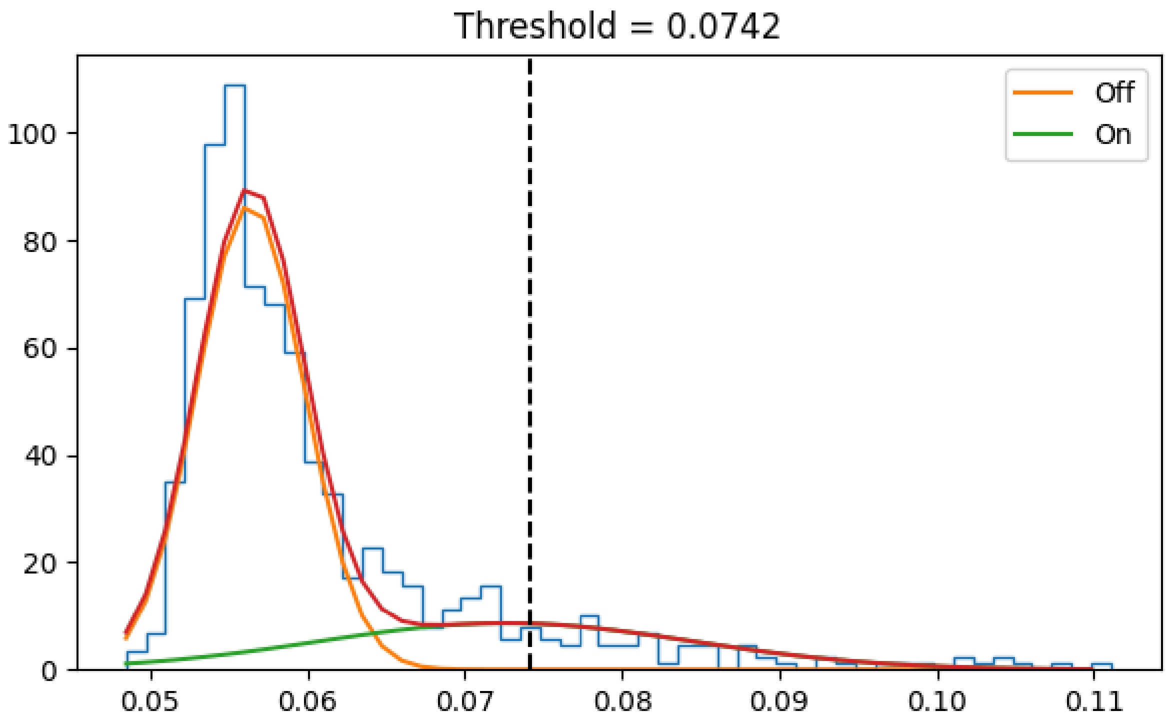

Threshold = 0.0525
Off
On
120
100
80
60
40
20
0
0.04
0.05
0.06
0.07
0.08

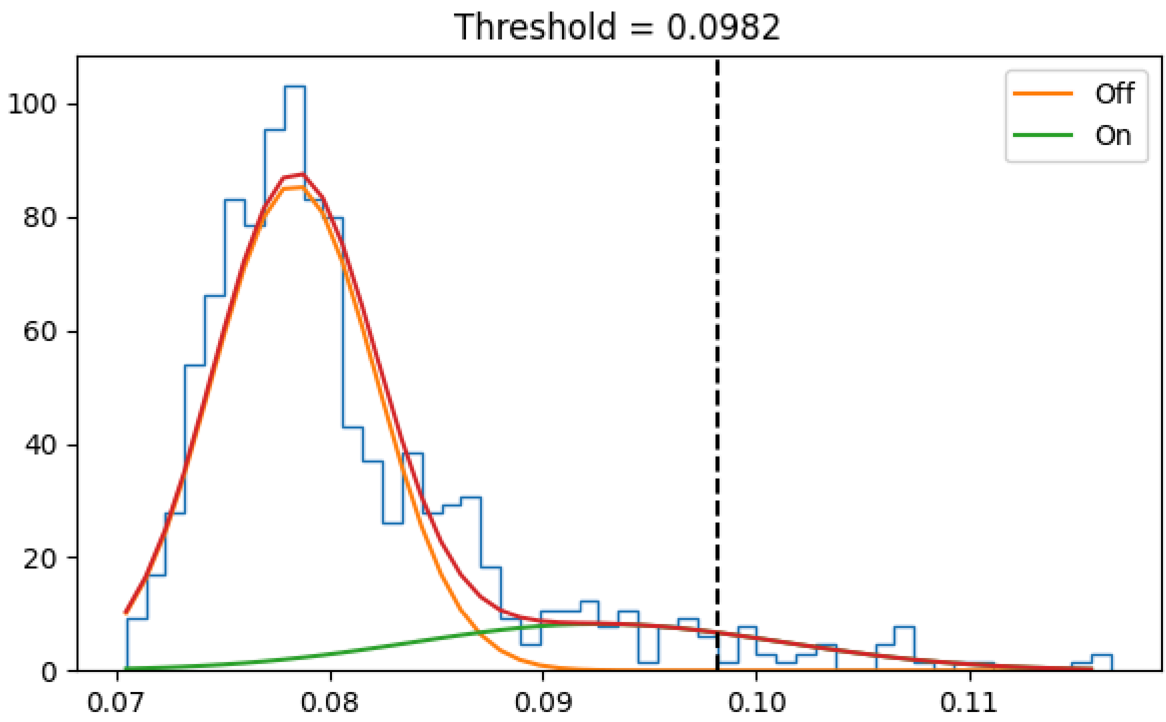

Threshold = 0.0603
Off
On
80
70
60
50
40
30
20
10
0
0.04
0.06
0.08
0.10
0.12

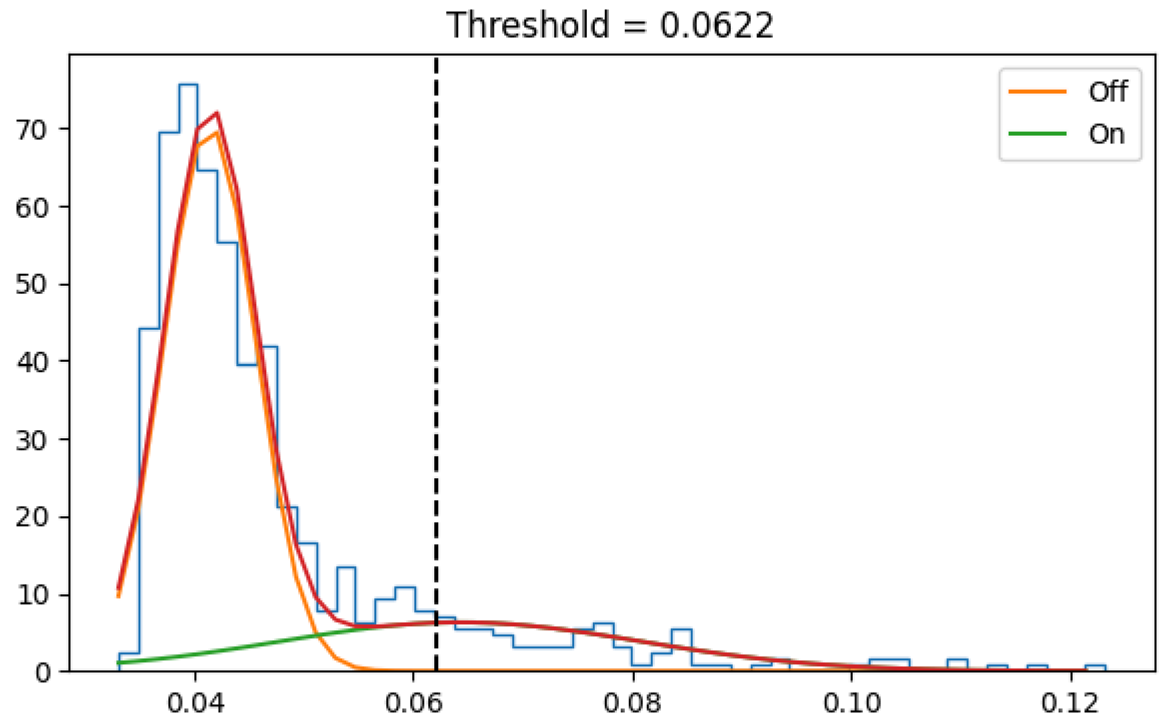

Threshold = 0.0699
Off
On
0
10
20
30
40
50
60
70
0.04
0.06
0.08
0.10
0.12


Threshold = 0.0616
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.05
0.06
0.07
0.08
0.09
0.10
0.11
0.12


Threshold = 0.0622
Off
On
0
10
20
30
40
50
60
70
80
0.04
0.06
0.08
0.10
0.12


Threshold = 0.0742
Off
On
0
20
40
60
80
100
0.05
0.06
0.07
0.08
0.09
0.10
0.11

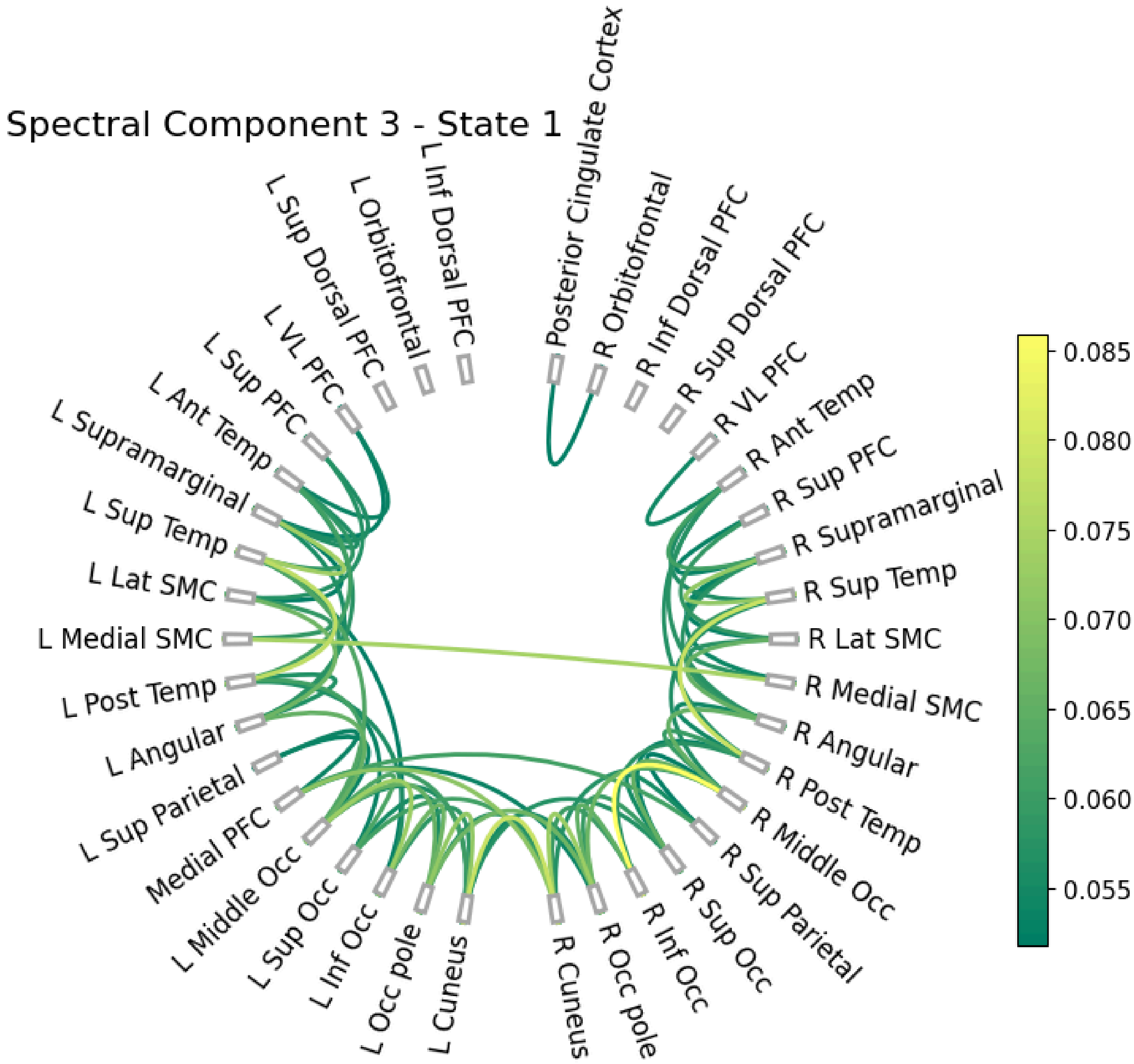




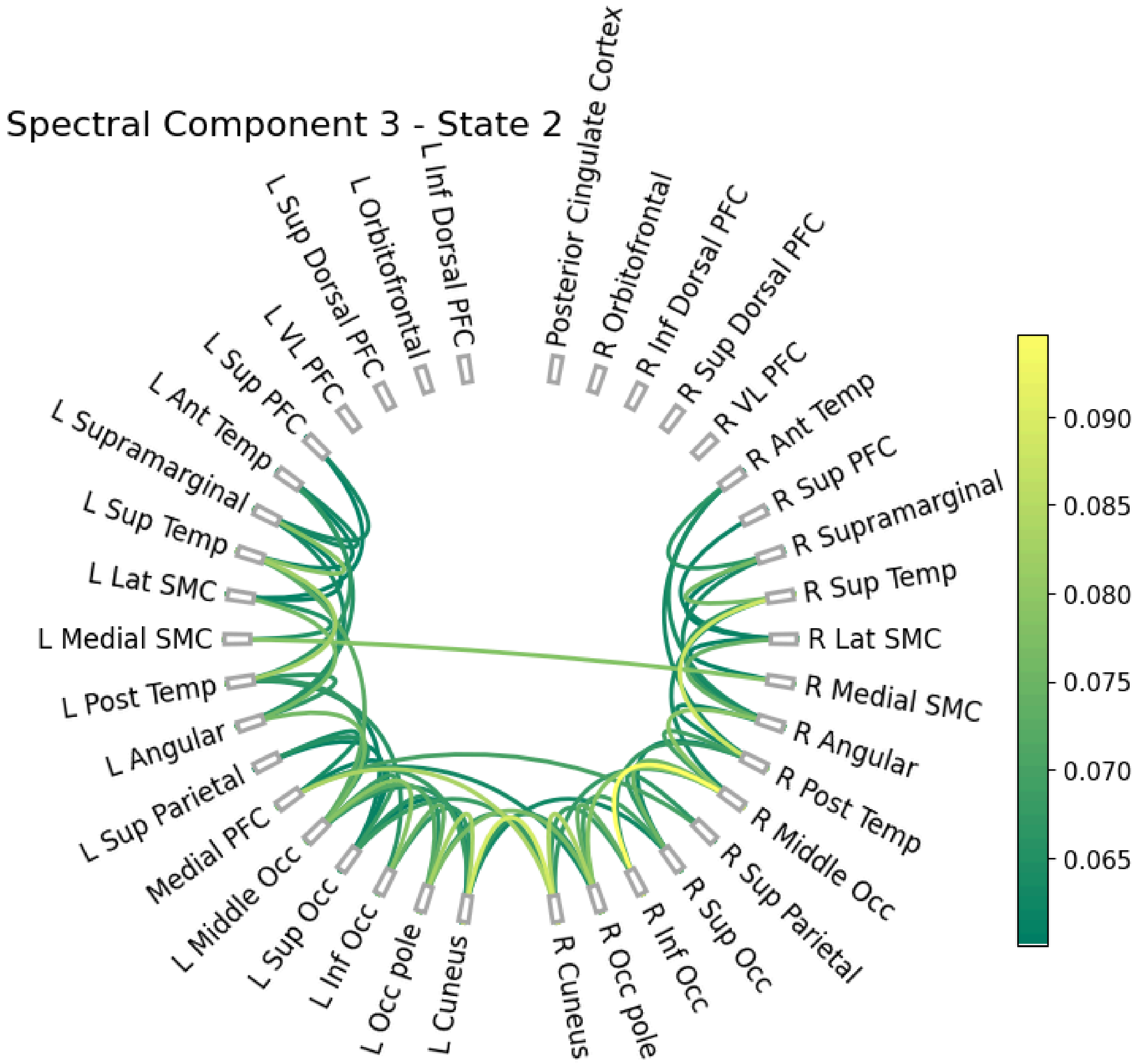
Spectral component 2

In [288…

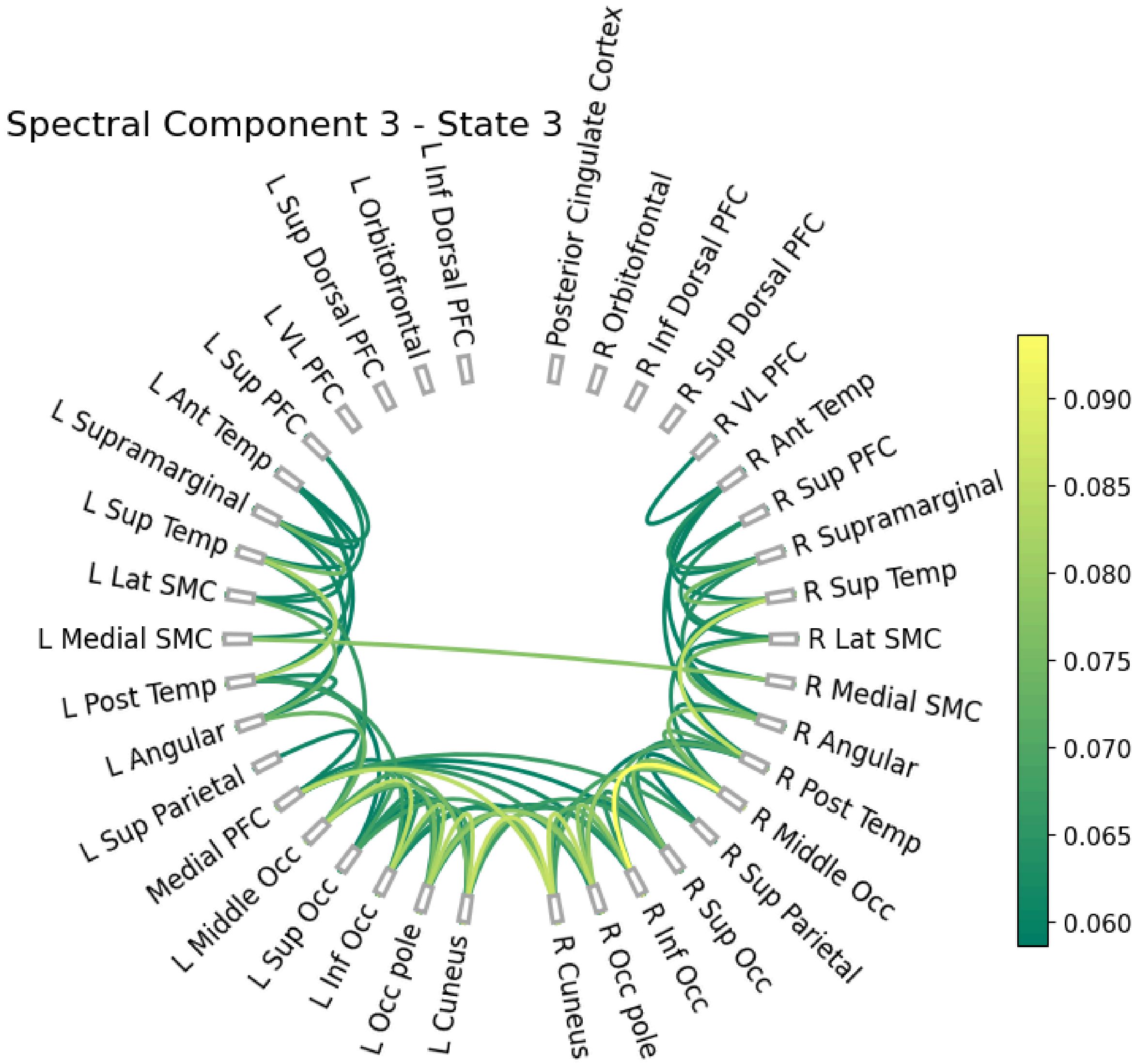
```
connectivity_6states_SC3_S1 = thres_mean_c[2][0]  # comp 3 state 1

sc=2
title = 'Spectral Component 3 - State 1
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```



In [289…
```
connectivity_6states_SC3_S2 = thres_mean_c[2][1]  # comp 3 state 2

sc=2
title = 'Spectral Component 3 - State 2
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```

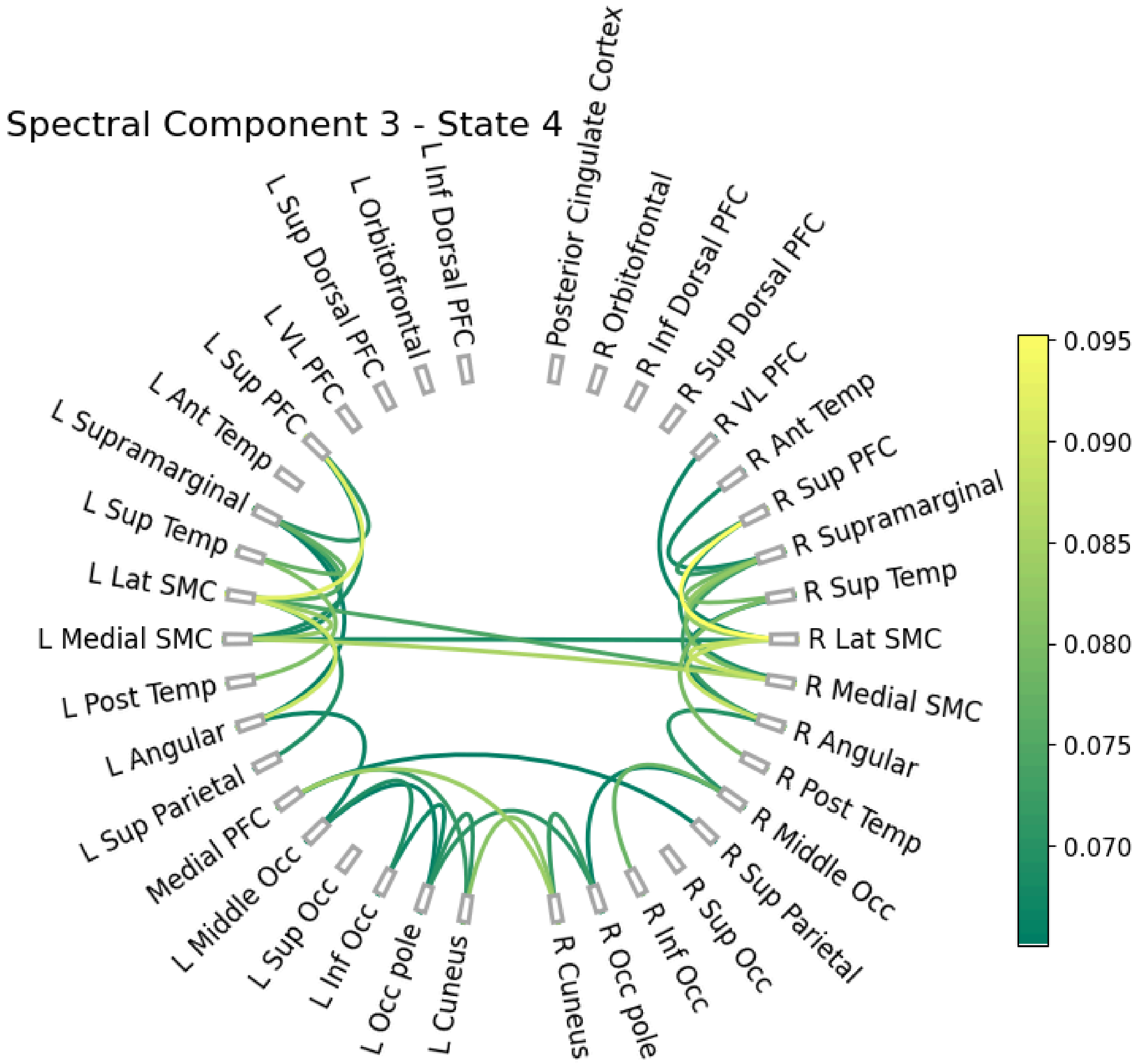


In [290…
```
connectivity_6states_SC3_S3 = thres_mean_c[2][2]  # comp 3 state 3

sc=2
title = 'Spectral Component 3 - State 3
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```



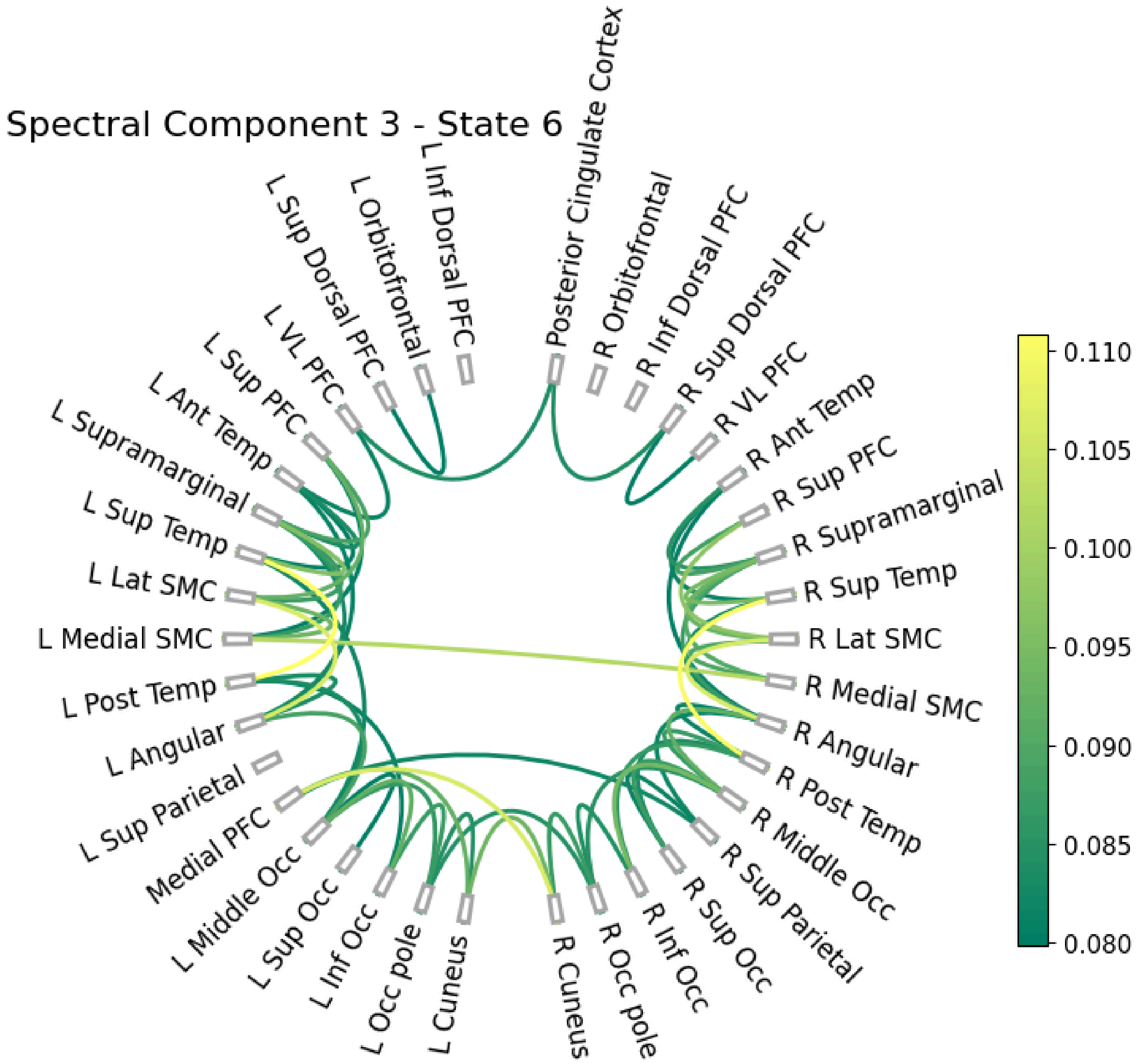
In [291…

```
connectivity_6states_SC3_S4 = thres_mean_c[2][3]  # comp 3 state 4

sc=2
title = 'Spectral Component 3 - State 4
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```



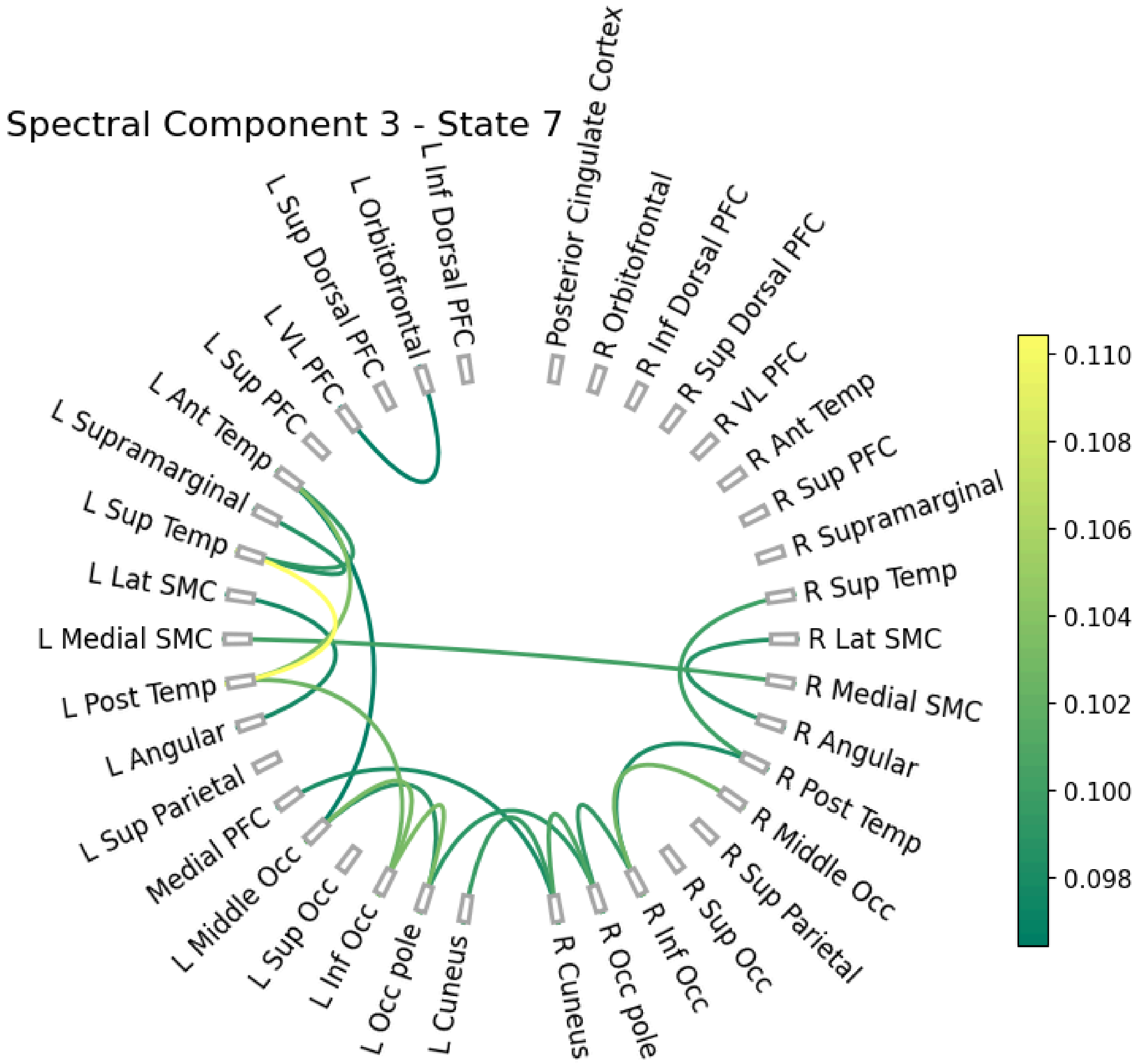
In [292…

```
connectivity_6states_SC3_S6 = thres_mean_c[2][4]   # comp 3 state 6

sc=2
title = 'Spectral Component 3 - State 6
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```



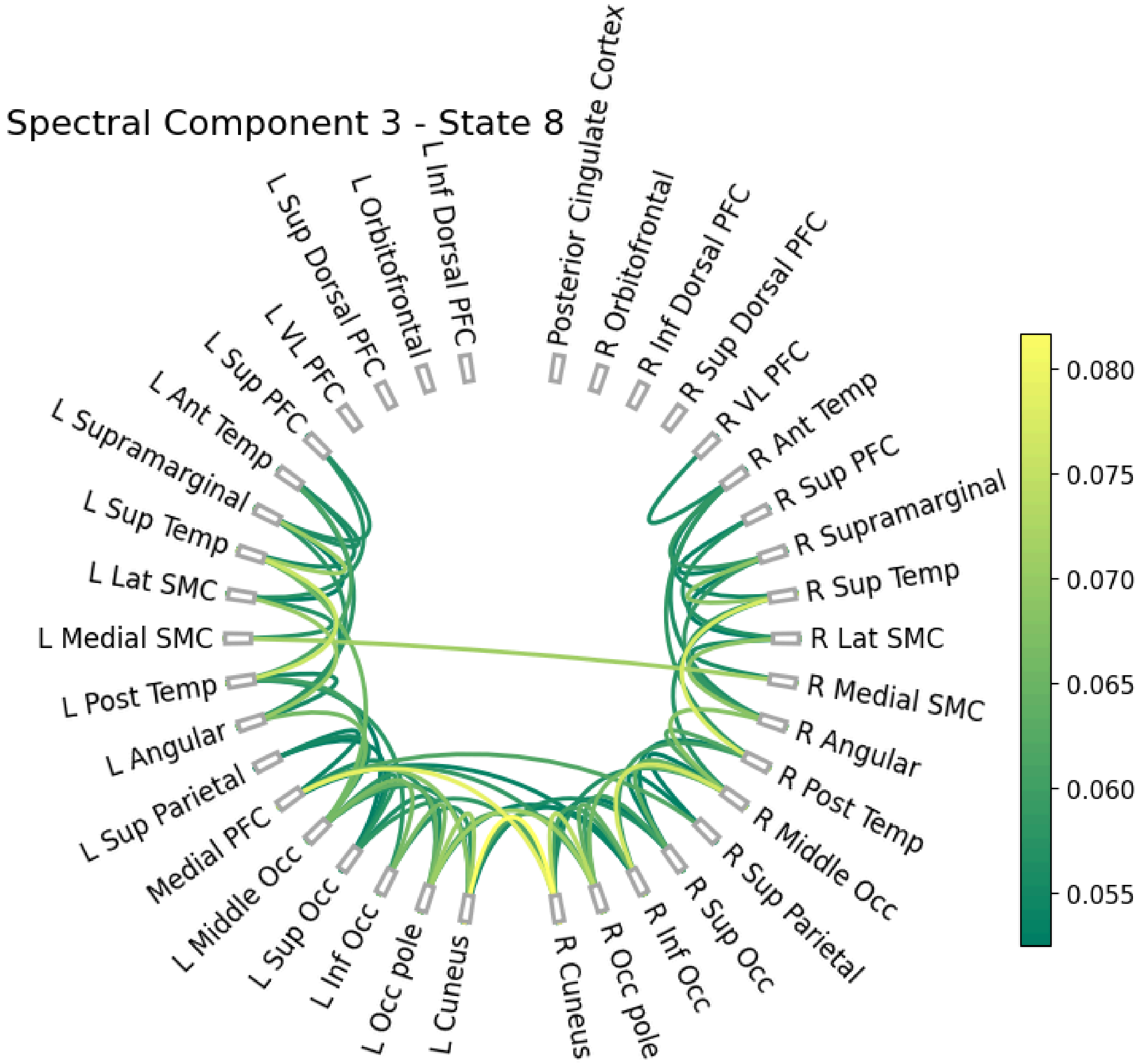
In [293…

```
connectivity_6states_SC3_S7 = thres_mean_c[2][5]   # comp 3 state 7

sc=2
title = 'Spectral Component 3 - State 7
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```



In [294…

```
connectivity_6states_SC3_S8 = thres_mean_c[2][6]   # comp 3 state 8

sc=2
title = 'Spectral Component 3 - State 8'
img_name = 'Spectral_Comp_' + str(sc+1) +'_State_.png'
plot_spatial_map_connectivity(connectivity_matrix=connectivity_6states_SC3_S
                              title=title, image_name=img_name, network=True
```


Spectral Component 3 - State 8
Posterior Cingulate Cortex
R Orbitofrontal
R Inf Dorsal PFC
R Sup Dorsal PFC
R VL PFC
R Ant Temp
R Sup PFC
R Supramarginal
R Sup Temp
R Lat SMC
R Medial SMC
R Angular
R Post Temp
R Middle Occ
R Sup Parietal
R Sup Occ
R Inf Occ
R Occ pole
R Cuneus
L Cuneus
L Occ pole
L Inf Occ
L Sup Occ
L Middle Occ
Medial PFC
L Sup Parietal
L Angular
L Post Temp
L Medial SMC
L Lat SMC
L Sup Temp
L Supramarginal
L Ant Temp
L Sup PFC
L VL PFC
L Sup Dorsal PFC
L Orbitofrontal
L Inf Dorsal PFC
0.080
0.075
0.070
0.065
0.060
0.055

In [ ]:

In [ ]: