

✓ Removing muscle ICA components

Gross movements produce widespread high-frequency activity across all channels that is usually not recoverable and so the epoch must be rejected as shown in `ex-muscle-artifacts`. More ubiquitously than gross movements, muscle artifact is produced during postural maintenance. This is more appropriately removed by ICA otherwise there wouldn't be any epochs left! Note that muscle artifacts of this kind are much more pronounced in EEG than they are in MEG.

```
# Authors: Alex Rockhill <aprockhill@mailbox.org>
#
# License: BSD-3-Clause
# Copyright the MNE-Python contributors.
```

```
import mne
```

```
data_path = mne.datasets.sample.data_path()
raw_fname = data_path / "MEG" / "sample" / "sample_audvis_raw.fif"
raw = mne.io.read_raw_fif(raw_fname)
raw.crop(tmin=100, tmax=130) # take 30 seconds for speed
```

```
# pick only EEG channels, muscle artifact is basically not picked up by MEG
# if you have a simultaneous recording, you may want to do ICA on MEG and EEG
# separately
raw.pick(picks="eeg", exclude="bads")
```

```
# ICA works best with a highpass filter applied
raw.load_data()
raw.filter(l_freq=1.0, h_freq=None)
```

📄 Opening raw data file C:\Users\ulewi\mne_data\MNE-sample-data\MEG\sample\sample_audvis_raw.fif...

Read a total of 3 projection items:

```
PCA-v1 (1 x 102) idle
PCA-v2 (1 x 102) idle
PCA-v3 (1 x 102) idle
```

Range : 25800 ... 192599 = 42.956 ... 320.670 secs

Ready.

Reading 0 ... 18019 = 0.000 ... 30.001 secs...

Filtering raw data in 1 contiguous segment

Setting up high-pass filter at 1 Hz

FIR filter parameters

Designing a one-pass, zero-phase, non-causal highpass filter:

- Windowed time-domain design (firwin) method
- Hamming window with 0.0194 passband ripple and 53 dB stopband attenuation
- Lower passband edge: 1.00
- Lower transition bandwidth: 1.00 Hz (-6 dB cutoff frequency: 0.50 Hz)
- Filter length: 1983 samples (3.302 s)

[Parallel(n_jobs=1)]: Done 17 tasks | elapsed: 0.0s

▼ General

Measurement date December 03, 2002 19:01:10 GMT

Experimenter MEG

Participant Unknown

▼ Channels

Digitized points 146 points

Good channels 59 EEG

Bad channels None

EOG channels Not available

ECG channels Not available

▼ Data

Sampling frequency 600.61 Hz

Highpass 1.00 Hz

Lowpass 172.18 Hz

Filenames sample_audvis_raw.fif

Duration 00:00:31 (HH:MM:SS)

Run ICA

```
ica = mne.preprocessing.ICA(
    n_components=15, method="picard", max_iter="auto", random_state=97
)
ica.fit(raw)
```

```

↳ Fitting ICA to data using 59 channels (please be patient, this may take a while)
Selecting by number: 15 components
Fitting ICA took 3.6s.

```

Method	picard
Fit parameters	max_iter=500
Fit	36 iterations on raw data (18020 samples)
ICA components	15
Available PCA components	59
Channel types	eeg
ICA components marked for exclusion	—

Remove components with postural muscle artifact using ICA

```
ica.plot_sources(raw)
```

```

↳ Creating RawArray with float64 data, n_channels=15, n_times=9760
Range : 0 ... 9759 = 0.000 ... 60.994 secs
Ready.
<mne_qt_browser._pg_figure.MNEQtBrowser at 0x1bf657a0f80>

```

By inspection, let's select out the muscle-artifact components based on :footcite: DharmapranjEtA12016 manually.

The criteria are:

- Positive slope of log-log power spectrum between 7 and 75 Hz (here just flat because it's not in log-log)
- Peripheral focus or dipole/multi-pole foci (the blue and red blobs in the topomap are far from the vertex where the most muscle is)
- Single focal point (low spatial smoothness; there is just one focus of the topomap compared to components like the first ones that are more likely neural which spread across the topomap)

The other attribute worth noting is that the time course in :func: mne.preprocessing.ICA.plot_sources looks like EMG; you can see spikes when each motor unit fires so that the time course looks fuzzy and sometimes has large spikes that are often at regular intervals.

ICA component 13 is a textbook example of what muscle artifact looks like. The focus of the topomap for this component is right on the temporalis muscle near the ears. There is also a minimum in the power spectrum at around 10 Hz, then a maximum at around 25 Hz, generally resulting in a positive slope in log-log units; this is a very typical pattern for muscle artifact.

```

idx = [0, 1, 2, 3, 4, 5, 6, 7]
ica.plot_properties(raw, picks=idx, log_scale=True)

```



Using multitaper spectrum estimation with 7 DPSS windows

Not setting metadata

30 matching events found

No baseline correction applied

0 projection items activated

Not setting metadata

30 matching events found

No baseline correction applied

0 projection items activated

Not setting metadata

30 matching events found

No baseline correction applied

0 projection items activated

Not setting metadata

30 matching events found

No baseline correction applied

0 projection items activated

Not setting metadata

30 matching events found

No baseline correction applied

0 projection items activated

Not setting metadata

30 matching events found

No baseline correction applied

0 projection items activated

Not setting metadata

30 matching events found

No baseline correction applied

0 projection items activated

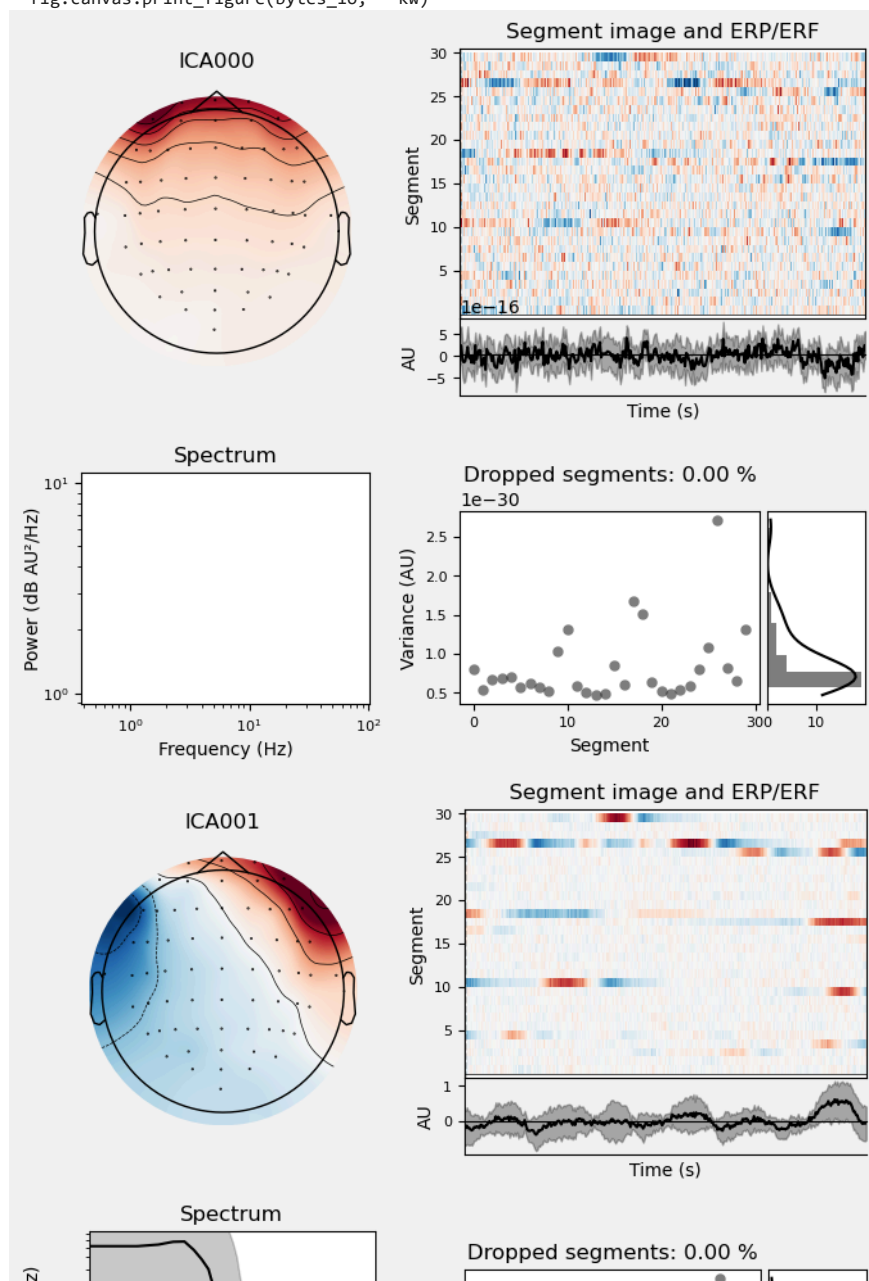
Not setting metadata

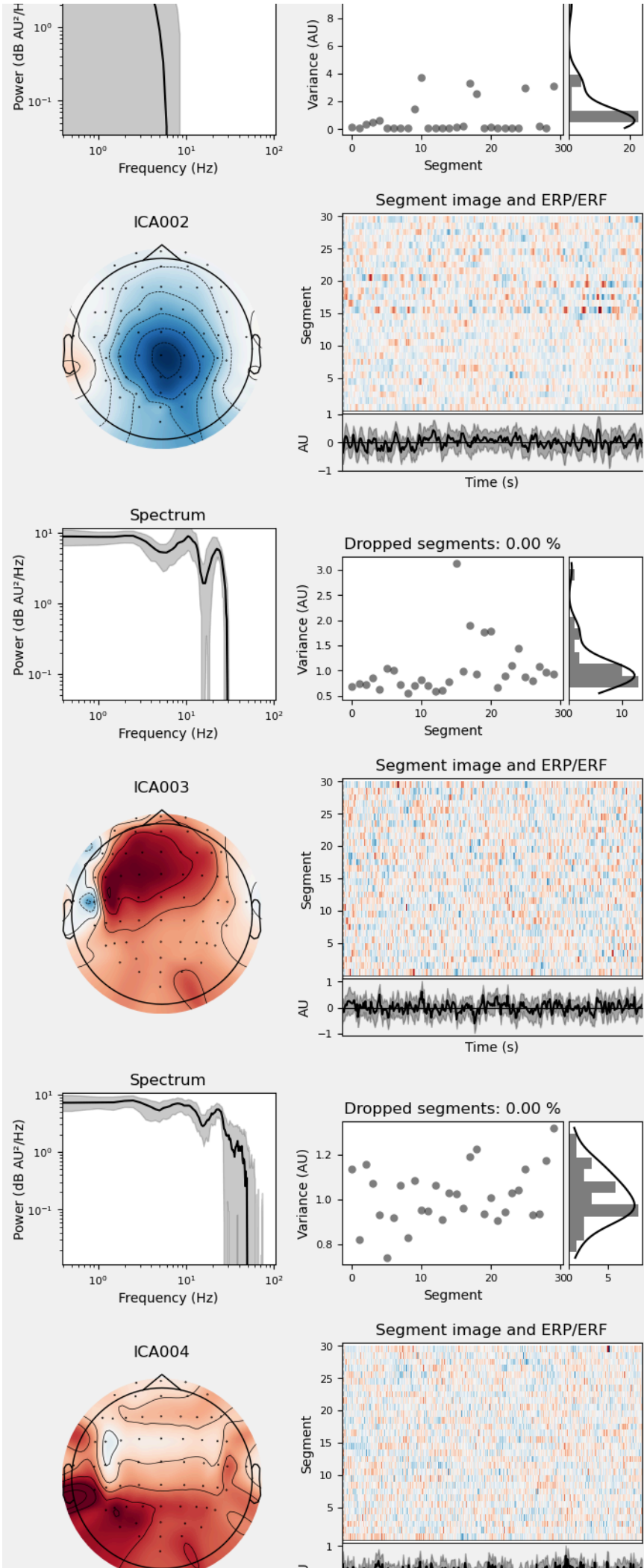
30 matching events found

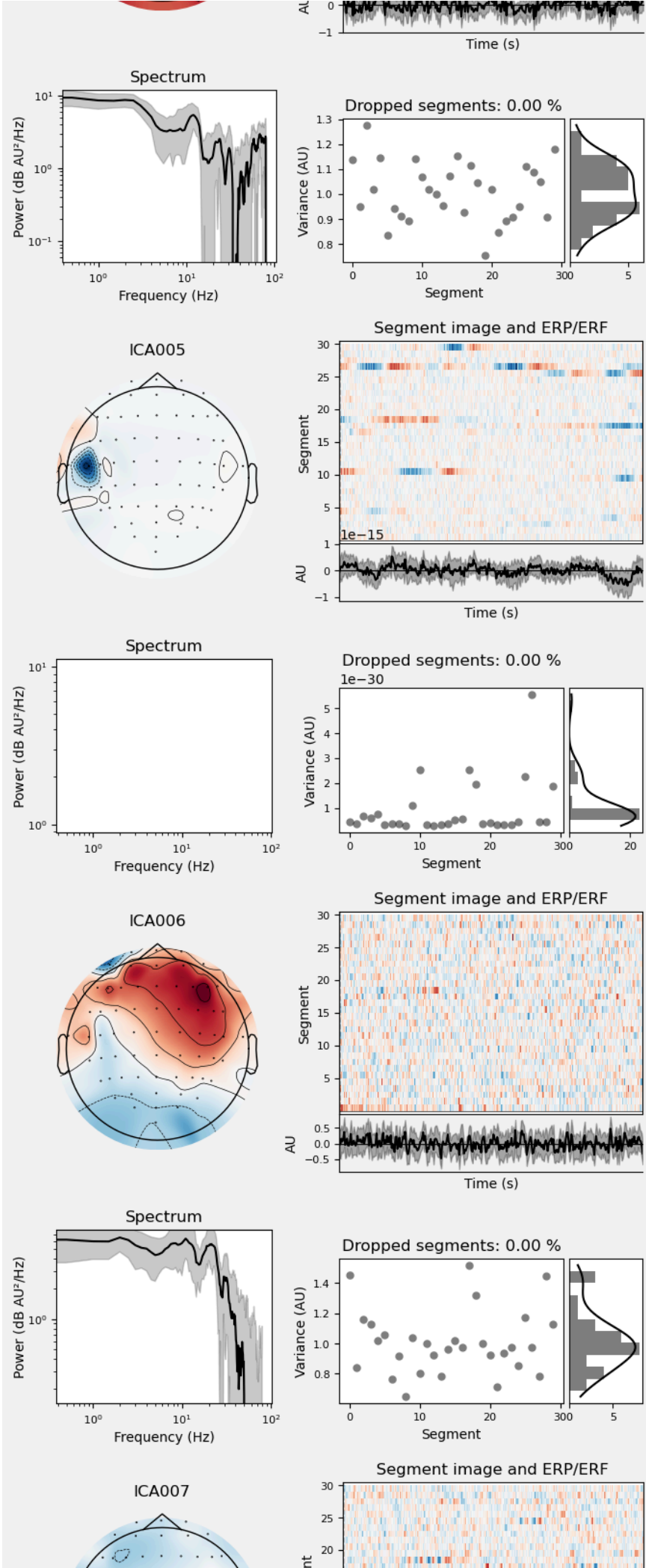
No baseline correction applied

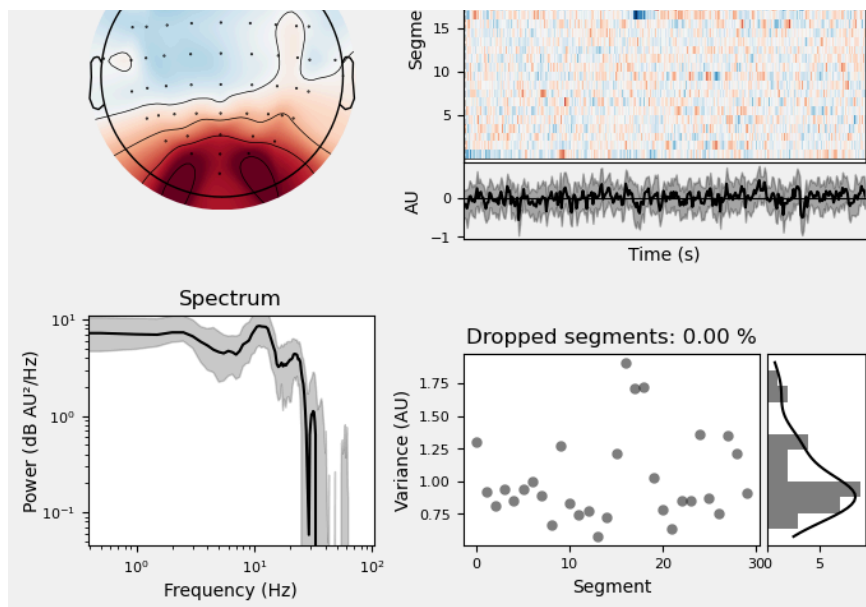
0 projection items activated

c:\Users\ulewi\mne-python\1.7.0_0\Lib\site-packages\IPython\core\pylabtools.py:152: U
fig.canvas.print_figure(bytes_io, **kw)





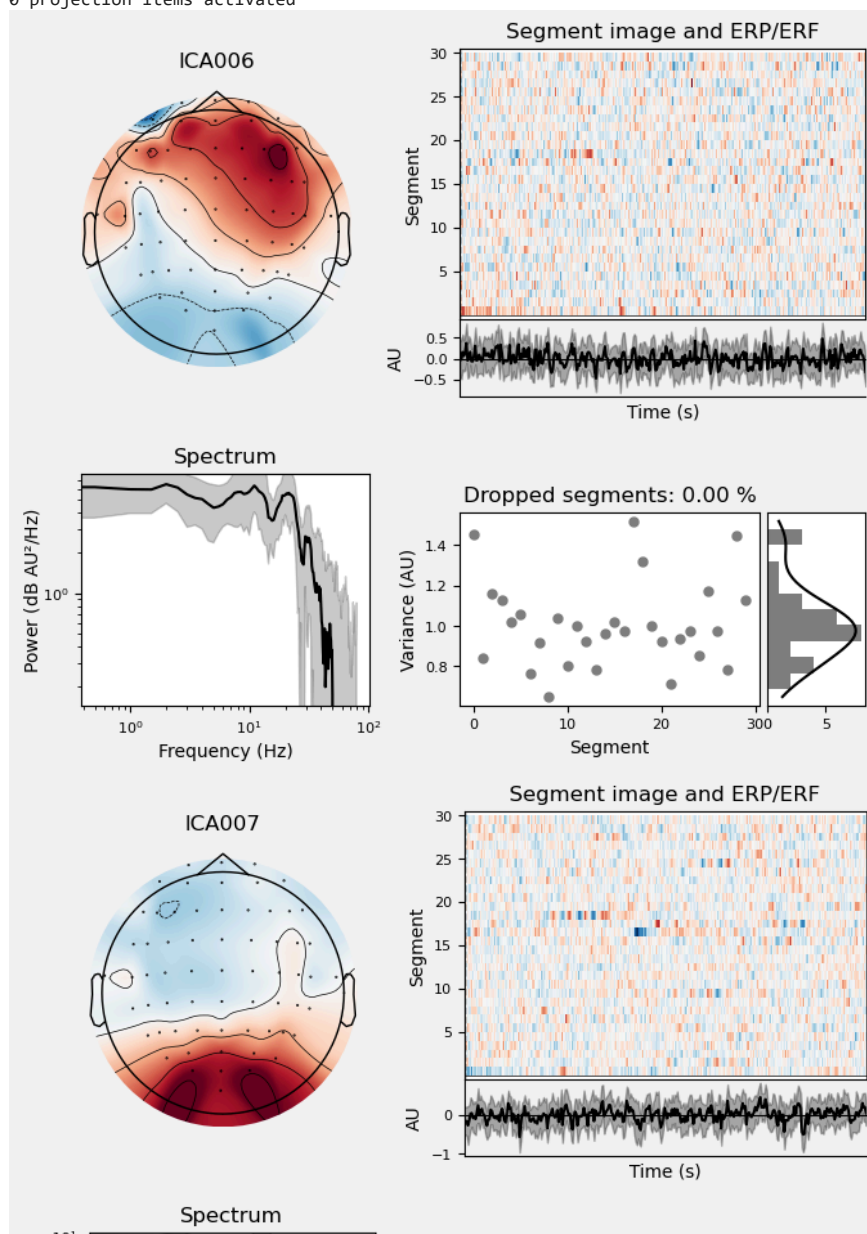


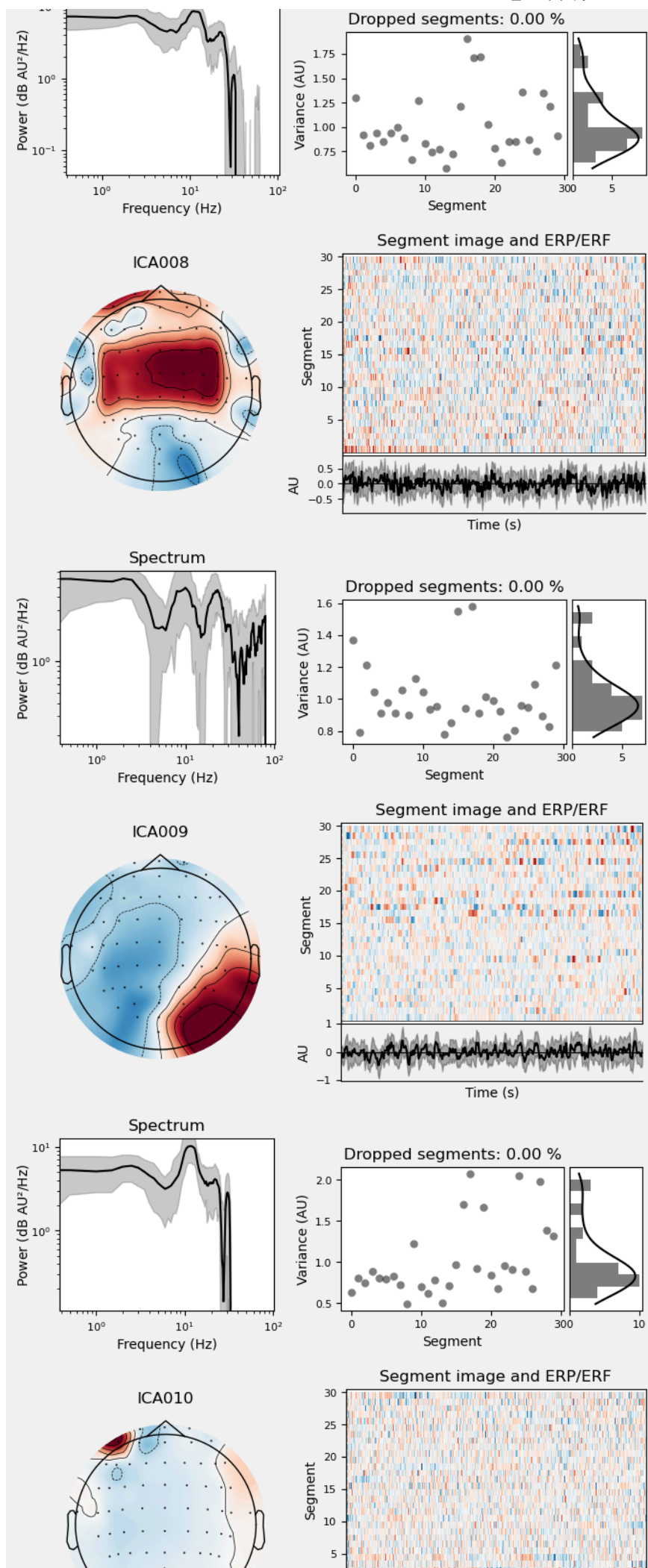


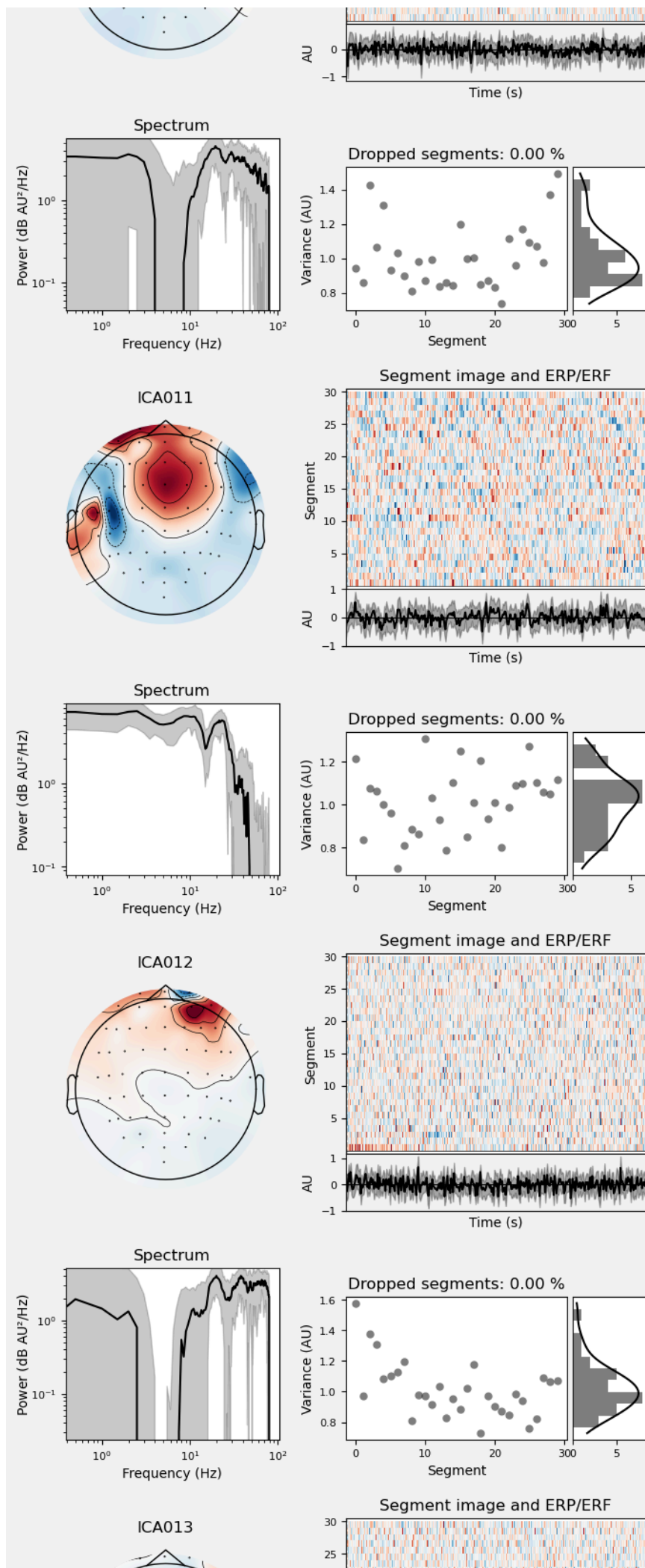
[<Figure size 700x600 with 6 Axes>,
 <Figure size 700x600 with 6 Axes>,
 <Figure size 700x600 with 6 Axes>,
 <Figure size 700x600 with 6 Axes>,
 <Figure size 700x600 with 6 Axes>,
 <Figure size 700x600 with 6 Axes>,
 <Figure size 700x600 with 6 Axes>,
 <Figure size 700x600 with 6 Axes>]

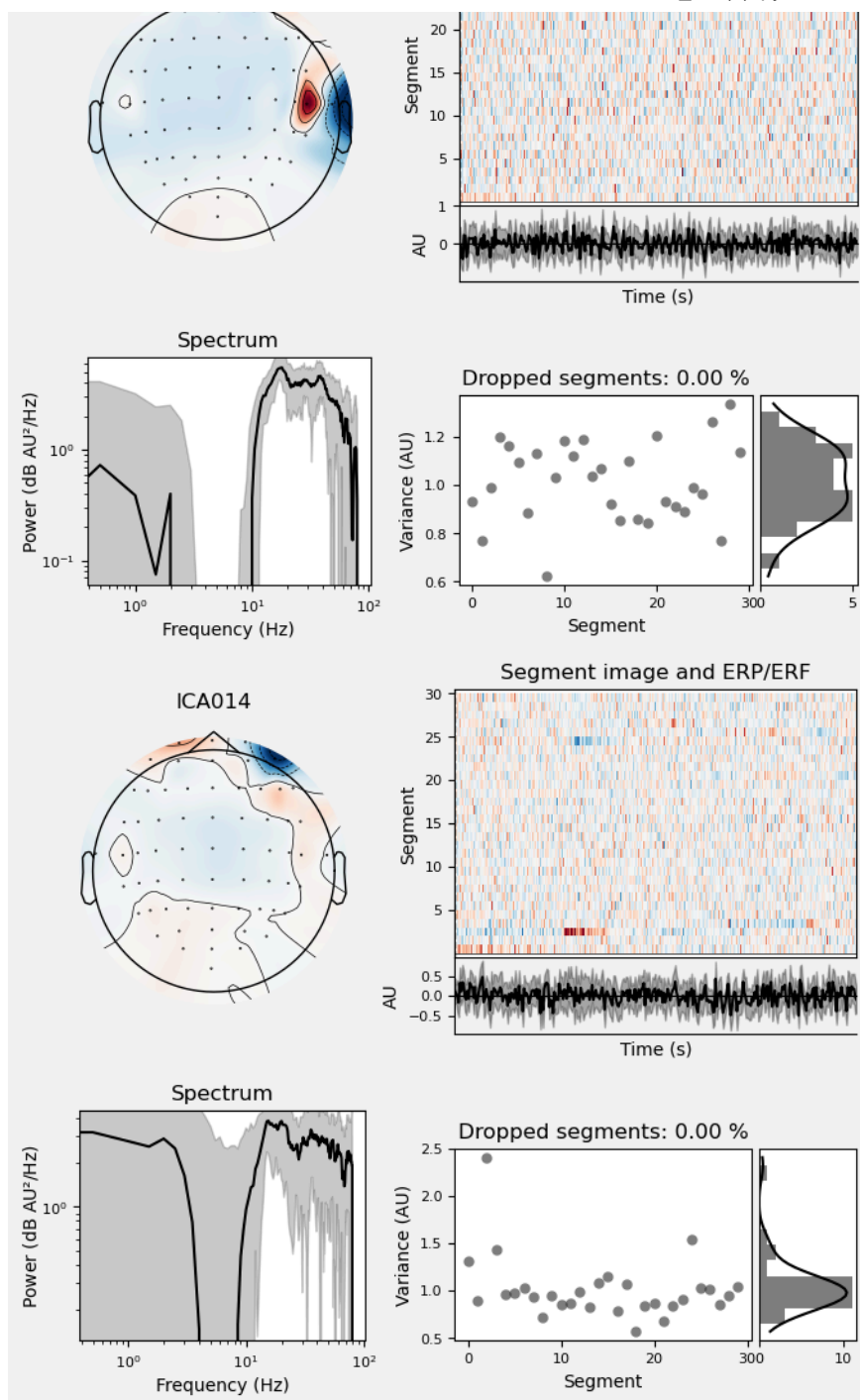
```
muscle_idx = [6, 7, 8, 9, 10, 11, 12, 13, 14]
ica.plot_properties(raw, picks=muscle_idx, log_scale=True)
```

```
# first, remove blinks and heartbeat to compare
blink_idx = [0]
heartbeat_idx = [5]
ica.apply(raw, exclude=blink_idx + heartbeat_idx)
ica.plot_overlay(raw, exclude=muscle_idx)
```

[illegible]

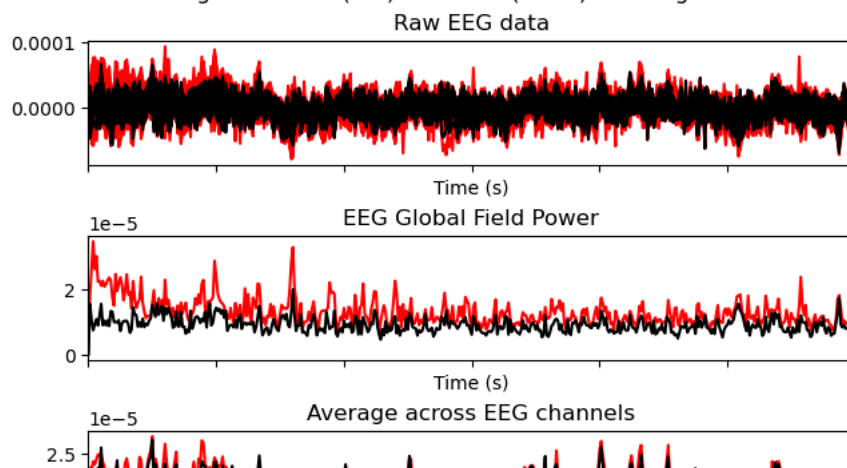


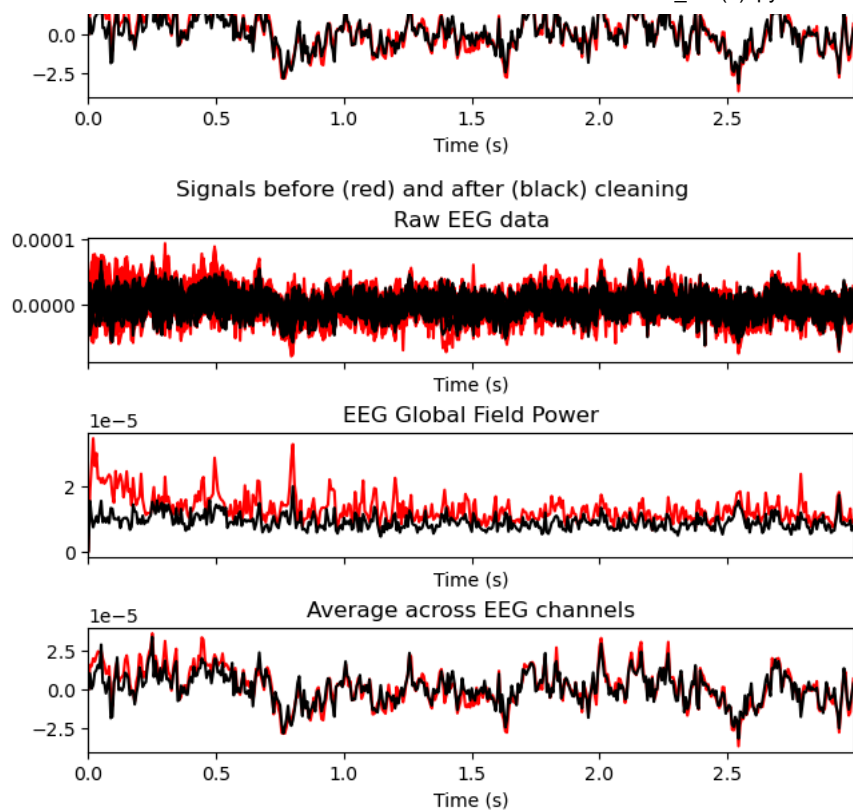




Applying ICA to Raw instance
 Transforming to ICA space (15 components)
 Zeroing out 2 ICA components
 Projecting back using 64 PCA components
 Applying ICA to Raw instance
 Transforming to ICA space (15 components)
 Zeroing out 9 ICA components
 Projecting back using 64 PCA components

Signals before (red) and after (black) cleaning

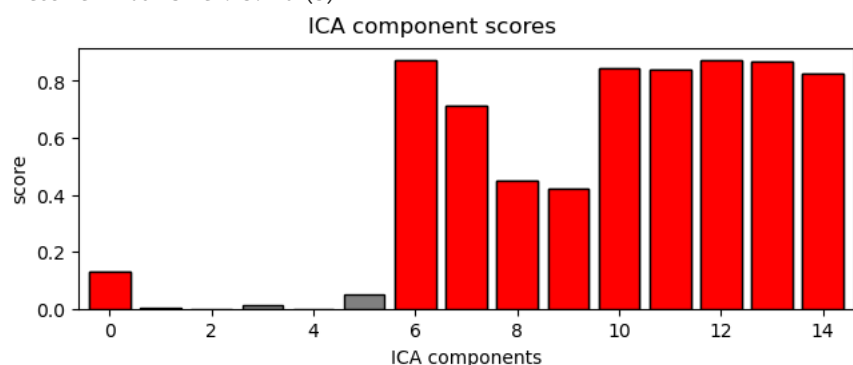




Finally, let's try an automated algorithm to find muscle components and ensure that it gets the same components we did manually.

```
muscle_idx_auto, scores = ica.find_bads_muscle(raw)
ica.plot_scores(scores, exclude=muscle_idx_auto)
print(
    f"Manually found muscle artifact ICA components: {muscle_idx}\n"
    f"Automatically found muscle artifact ICA components: {muscle_idx_auto}"
)
```

Effective window size : 3.410 (s)



Manually found muscle artifact ICA components: [6, 7, 8, 9, 10, 11, 12, 13, 14]
 Automatically found muscle artifact ICA components: [0, 6, 7, 8, 9, 10, 11, 12, 13, 14]

✓ Let's now replicate this on the EEGBCI dataset

```
for sub in (1, 2):
    raw = mne.io.read_raw_edf(
        mne.datasets.eegbci.load_data(subject=sub, runs=(1,))[0], preload=True
    )
    mne.datasets.eegbci.standardize(raw) # set channel names
    montage = mne.channels.make_standard_montage("standard_1005")
    raw.set_montage(montage)
    raw.filter(l_freq=1.0, h_freq=None)

    # Run ICA
    ica = mne.preprocessing.ICA(
        n_components=15, method="picard", max_iter="auto", random_state=97
    )
    ica.fit(raw)
    ica.plot_sources(raw)
    muscle_idx_auto, scores = ica.find_bads_muscle(raw)
    ica.plot_properties(raw, picks=muscle_idx_auto, log_scale=True)
    ica.plot_scores(scores, exclude=muscle_idx_auto)

    print(
        f"Manually found muscle artifact ICA components:      {muscle_idx}\n"
        "Automatically found muscle artifact ICA components: "
        f"{muscle_idx_auto}"
    )
```

```

Using default location ~/mne_data for EEGBCI...
Downloading EEGBCI data
Downloading file 'S001/S001R01.edf' from 'https://physionet.org/files/eeegmidb/1.0.0/
Download complete in 26s (1.2 MB)
Extracting EDF parameters from C:\Users\ulewi\mne_data\MNE-eeegbci-data\files\eeegmidb
EDF file detected
Setting channel info structure...
Creating raw.info structure...
Reading 0 ... 9759 = 0.000 ... 60.994 secs...
Filtering raw data in 1 contiguous segment
Setting up high-pass filter at 1 Hz

```

FIR filter parameters

Designing a one-pass, zero-phase, non-causal highpass filter:

- Windowed time-domain design (firwin) method
- Hamming window with 0.0194 passband ripple and 53 dB stopband attenuation
- Lower passband edge: 1.00
- Lower transition bandwidth: 1.00 Hz (-6 dB cutoff frequency: 0.50 Hz)
- Filter length: 529 samples (3.306 s)

Fitting ICA to data using 64 channels (please be patient, this may take a while)

[Parallel(n_jobs=1)]: Done 17 tasks | elapsed: 0.0s

Selecting by number: 15 components

Fitting ICA took 2.2s.

Creating RawArray with float64 data, n_channels=15, n_times=9760

Range : 0 ... 9759 = 0.000 ... 60.994 secs

Ready.

Effective window size : 12.800 (s)

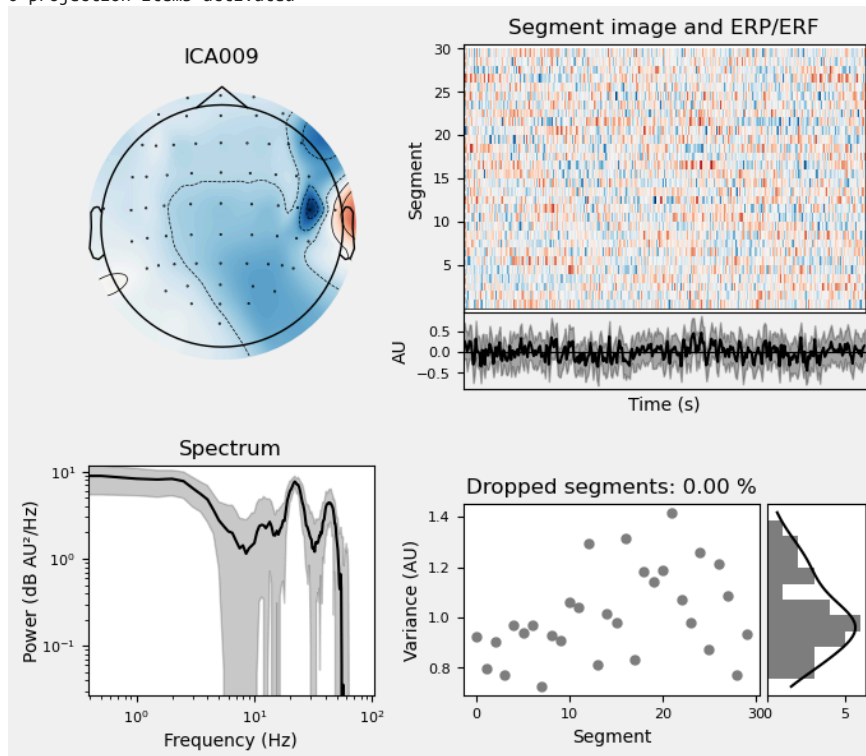
Using multitaper spectrum estimation with 7 DPSS windows

Not setting metadata

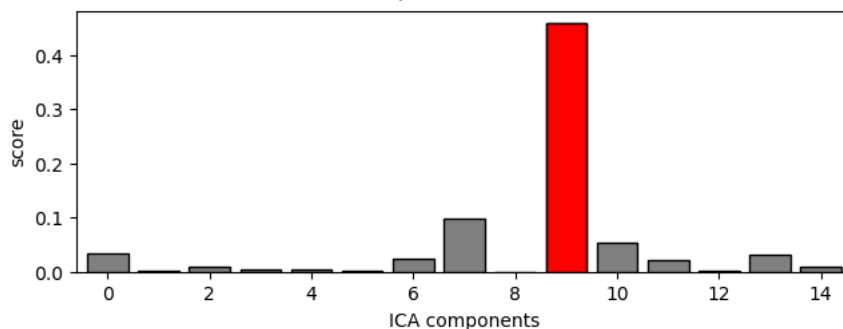
30 matching events found

No baseline correction applied

0 projection items activated



ICA component scores



Manually found muscle artifact ICA components: [6, 7, 8, 9, 10, 11, 12, 13, 14]

Automatically found muscle artifact ICA components: [9]

Downloading EEGBCI data

Downloading file 'S002/S002R01.edf' from 'https://physionet.org/files/eeegmidb/1.0.0/

Download complete in 03s (1.2 MB)

Extracting EDF parameters from C:\Users\ulewi\mne_data\MNE-eeegbci-data\files\eeegmidb

EDF file detected

```

Setting channel info structure...
Creating raw.info structure...
Reading 0 ... 9759 = 0.000 ... 60.994 secs...
Filtering raw data in 1 contiguous segment
Setting up high-pass filter at 1 Hz

FIR filter parameters
-----
Designing a one-pass, zero-phase, non-causal highpass filter:
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Fitting ICA to data using 64 channels (please be patient, this may take a while)
[Parallel(n_jobs=1)]: Done 17 tasks | elapsed: 0.0s
Selecting by number: 15 components
Fitting ICA took 2.2s.
Creating RawArray with float64 data, n_channels=15, n_times=9760
Range : 0 ... 9759 = 0.000 ... 60.994 secs
Ready.
Effective window size : 12.800 (s)
Using multitaper spectrum estimation with 7 DPSS windows
Not setting metadata
30 matching events found
No baseline correction applied
0 projection items activated
Not setting metadata
30 matching events found
No baseline correction applied
0 projection items activated
Not setting metadata
30 matching events found
No baseline correction applied
0 projection items activated
Not setting metadata
30 matching events found
No baseline correction applied
0 projection items activated
Not setting metadata
30 matching events found
No baseline correction applied
0 projection items activated
Not setting metadata
30 matching events found
No baseline correction applied
0 projection items activated

```

