session_demonstration_script

November 26, 2021

1 Example code for using session.Session

Note: This notebook covers several relevant methods of the `Session` and `Stim` objects, detailing some of their arguments, as well. For more details, take a look at the docstring associated with a method of interest.

Import notes:

- These packages should be present if installing the conda environment from `osca.yml`.
- `util` is a Github repo of mine, and the correct branch `osca_mult` is automatically installed from `osca.yml`.

- **Potential updates:** Errors internal to the codebase involving `util` code and occurring *after* new changes have been pulled from the `OpenScope_CA_Analysis` repo *may* be due to an update of the `osca_mult` branch of `util` that breaks backwards compatibility.
  Though I will try to avoid this, check whether there are updates to the utility, if an error occurs, and consider updating your installation, e.g., by running, from the command line: `pip install -U util-colleenjg`

[1]:
```
import sys
from pathlib import Path

from matplotlib import pyplot as plt
import numpy as np
import pandas as pd

sys.path.extend([".", ".."])
from analysis import session
from sess_util import sess_gen_util, sess_plot_util
from util import gen_util, logger_util, plot_util
```

1.1 Plot formatting

If you wish to use the same formatting style as I do:

[2]:
```
plot_util.linclab_plt_defaults()
```

1.2 Set paths to main data directory and the mouse dataframe

1.2.1 Data directory

The data directory should contain the session data, either in its **original format** or in **NWB format**.
* If in NWB format (production data, only), `datadir` should be a directory that contains the data in NWB format, at any depth.
* If using the data in its original format, `datadir` should specifically be the directory right before the data is split into `prod` (production) and `pilot` (pilot) data.

[3]:
```
datadir = Path("..", "..", "data", "OSCA")
```

1.2.2 Mouse dataframe

The mouse dataframe, contains the metadata for each session, including its 9-digit `sessid`, the `mouse_n`, `sess_n`, etc.

[4]:
```
mouse_df = pd.read_csv(Path("..", "mouse_df.csv"))
```

Mouse dataframe columns:
* **`sessid`**: Unique session ID (9-digit)
* **`dandi_session_id`**: Dandiset session ID for data in NWB format.
* **`mouse_n`**: Mouse number
* **`mouseid`**: Unique mouse ID (6-digit)
* **`date`**: Recording date
* **`depth`**: Recording depth (um)
* **`plane`**: Recording plane ("dend" or "soma")
* **`line`**: Cell line ("L2/3-Cux2" or "L5-Rbp4")
* **`runtype`**: Type of session ("pilot" or "prod"). Only production data is available in NWB dataset.
* **`sess_n`**: Session number
* **`nrois`**: Number of valid ROIs (see ***Note***)
* **`nrois_tracked`**: Number of ROIs tracked across sessions (-1 for sessions with no tracking).
* **`nrois_all`**: Same as **`nrois`**, but including bad (non valid) ROIs.
* **`nrois_allen`**: Number of valid ROIs when using the `allen` segmentation for dendritic ROIs, instead of the `extr` segmentation (see ***Note***).
* **`nrois_allen_all`**: Same as **`nrois_allen`**, but including bad (non valid) ROIs.
* **`pass_fail`**: Whether the session passed (`P`) or failed (`F`) quality control.
* **`all_files`**: Whether all files are available for the session (original data format).
* **`any_files`**: Whether any files are available for the session (original data format).
* **`incl`**: Whether the session can be included in analyses (looser criterion than **`pass_fail`**).
* **`stim_seed`**: Seed used to initialize stimuli for the session, during recording.
* **`notes`**: Any notes on the session.

Note: The `allen` segmentations are used for all **somatic** data. The `extr` segmentations are preferred for all **dendritic** data. For this reason, the `allen` segmentation for **dendritic** data is ***not included*** in the NWB dataset. See **section 6** for details on `allen` and `extr` ROI mask types.

[5]:
```
mouse_df
```

```
[5]:       sessid dandi_session_id  mouse_n  mouseid      date  depth plane  \
    0   712483302              NaN        1   389778  20180621     20  dend
    1   712942208              NaN        1   389778  20180622    375  soma
    2   714893802              NaN        1   389778  20180627     20  dend
    3   715244457              NaN        1   389778  20180628     20  dend
    4   716425232              NaN        1   389778  20180702    375  soma
    ..        …              …      …      …        …     …    …
    78  833704570              NaN       13   440889  20190307    175  soma
    79  834403597  20190314T152429       13   440889  20190308    175  soma
    80  836968429  20190314T152429       13   440889  20190314    175  soma
    81  837360280  20190315T152224       13   440889  20190315    175  soma
    82  838633305              NaN       13   440889  20190318    175  soma

            line runtype  sess_n  …  nrois_tracked  nrois_all  nrois_allen  \
    0    L5-Rbp4   pilot       1  …             -1       1468          232
    1    L5-Rbp4   pilot       2  …             -1         78           62
    2    L5-Rbp4   pilot       3  …             -1         -1           -1
    3    L5-Rbp4   pilot       4  …             -1        949          458
    4    L5-Rbp4   pilot       5  …             -1         79           56
    ..       …       …     …  …             …          …           …
    78  L23-Cux2    prod       2  …            147        251          224
    79  L23-Cux2    prod       3  …            147        228          210
    80  L23-Cux2    prod       4  …             -1        217          205
    81  L23-Cux2    prod       5  …             -1        244          217
    82  L23-Cux2    prod       6  …             -1        256          227

        nrois_allen_all  pass_fail all_files  any_files  incl stim_seed  \
    0               259          F         1          1   yes       103
    1                78          F         1          1   yes       103
    2                -1          F         0          1    no       103
    3               504          P         1          1   yes       103
    4                79          P         1          1   yes       103
    ..              …          …         …         …   …        …
    78              251          P         1          1   yes     16745
    79              228          P         1          1   yes     10210
    80              217          P         1          1   yes     24253
    81              244          F         1          1   yes     19576
    82              256          F         1          1    no     30582

                                                    notes
    0   dropped beh and eye tracking frames (7), stim …
    1   dropped beh and eye tracking frames (6), stim …
    2                 missing 2P recordings and ROI traces
    3                                                  NaN
    4                                                  NaN
    ..                                                 …
    78  stim2twop alignment shifted corrected with 2nd…
```

```
79   dropped beh and eye tracking frames (6), stim …
80   FOV shifted (poor alignment with previous sess…
81                                     z-drift (14 um)
82                           laser wavelength set to 800 um

[83 rows x 21 columns]
```

1.3 1. Basics of initializing a Session object

Sessions can be intialized with their 9-digit `sessid`:

[6]:
```python
sess = session.Session(764704289, datadir=datadir, mouse_df=mouse_df)
```

or with their `mouse_n`, `sess_n` and `runtype`:

[7]:
```python
sess = session.Session(mouse_n=6, sess_n=1, runtype="prod", datadir=datadir,␣
↪mouse_df=mouse_df)
```

1.3.1 Data format is identified automatically

During initialization, the code looks first for the session data in NWB format, under its `dandi_session_id`. If it doesn't find it, it looks for the data in its original format. If neither are found, an error is thrown.

1.3.2 Loading the data after initialization.

After creating the session, you must run `self.extract_info()`. This wasn't amalgamated into the `__init__` to reduce the amount of information needed to just create a session object.

1.3.3 Loading ROI/running/pupil info

You can load this information when you call `self.extract_info()` or manually later by calling `self.load_roi_info()`, `self.load_run_data()` and `self.load_pup_data()`.

[8]:
```python
sess.extract_info(full_table=False, roi=True, run=True, pupil=True)
```

```
Loading stimulus and alignment info…
Loading ROI trace info…
Loading running info…
    WARNING: Session 764704289: 211 dropped running frames (~0.1%) (in pre-
processing).
Loading pupil info…
```

1.3.4 Stimulus dataframe

The stimulus dataframe, stored under `sess.stim_df`, details the stimulus feature for each segment of the presentation.
A **segment** is the minimal subdivision of the stimulus presentation: **0.3 sec** for the Gabor stimulus, and **1s** for the visual flow, and grayscreen stimuli.

If a feature **does not apply** to certain segments (e.g., `gabor_number` for visual flow stimulus segments), the values for those segments will be `None`, `NaN` or `[]`, depending on the column's datatype.

Missing columns: Note that a few columns are missing, since the session was loaded with `full_table=False`. * `"gabor_orientations"`: Specific orientation of each Gabor patch, for each segment. * `"square_locations_x"`: Specific x location of each visual flow square, at **each frame** of each segment. * `"square_locations_y"`: Specific y location of each visual flow square, at **each frame** of each segment.

This is primarily to save memory, when loading a session, as this information is not typically needed. To load all columns, re-run `sess.extract_info()` with `full_table=True`. Data that is already loaded will not be re-loaded.

[9]:
```
sess.stim_df
```

[9]:
```
     stimulus_type stimulus_template_name  unexpected gabor_frame  \
0       grayscreen             grayscreen         NaN
1           gabors                 gabors         0.0           A
2           gabors                 gabors         0.0           B
3           gabors                 gabors         0.0           C
4           gabors                 gabors         0.0           D
…              …                      …          …           …
8839       visflow          visflow_right         0.0
8840       visflow          visflow_right         1.0
8841       visflow          visflow_right         1.0
8842       visflow          visflow_right         1.0
8843    grayscreen             grayscreen         NaN

      gabor_kappa  gabor_mean_orientation  gabor_number  \
0             NaN                     NaN           NaN
1            16.0                   135.0          30.0
2            16.0                   135.0          30.0
3            16.0                   135.0          30.0
4            16.0                   135.0          30.0
…            …                      …            …
8839          NaN                     NaN           NaN
8840          NaN                     NaN           NaN
8841          NaN                     NaN           NaN
8842          NaN                     NaN           NaN
8843          NaN                     NaN           NaN

                                       gabor_locations_x  \
0                                                     []
1     [-957.5664595131418, -573.877007228148, 789.96…
2     [-628.4848961265818, 341.7183469416823, 321.20…
3     [683.6508663589163, -890.7309000633387, -754.8…
4     [579.5453003762645, -499.8681800025132, -951.1…
…                                                    …
```

```
8839                                                []
8840                                                []
8841                                                []
8842                                                []
8843                                                []

                                      gabor_locations_y  \
0                                                   []
1     [-523.4450587378464, 22.61763399099607, -287.1…
2     [-122.57399381760757, -198.4686150995812, 203…
3     [-270.11244158601005, 574.7874674037628, -168…
4     [322.1656471050667, 97.49426011674268, 244.289…
…                                                 …
8839                                                []
8840                                                []
8841                                                []
8842                                                []
8843                                                []

                                        gabor_sizes  …  \
0                                                []  …
1     [293, 392, 392, 323, 280, 396, 316, 363, 226, …  …
2     [313, 319, 262, 228, 400, 210, 264, 218, 308, …  …
3     [396, 212, 277, 210, 390, 329, 406, 317, 358, …  …
4     [326, 244, 208, 212, 251, 242, 341, 299, 406, …  …
…                                                 …  …
8839                                                []  …
8840                                                []  …
8841                                                []  …
8842                                                []  …
8843                                                []  …

     square_proportion_flipped start_frame_stim  stop_frame_stim  \
0                          NaN                0             1800
1                          NaN             1800             1818
2                          NaN             1818             1836
3                          NaN             1836             1854
4                          NaN             1854             1872
…                          …                …                …
8839                      0.00           249960           250020
8840                      0.25           250020           250080
8841                      0.25           250080           250140
8842                      0.25           250140           250200
8843                       NaN           250200           251999

      num_frames_stim  start_frame_twop  stop_frame_twop  num_frames_twop  \
0                1800               143             1046              903
```

```
1                    18            1046           1055             9
2                    18            1055           1064             9
3                    18            1064           1073             9
4                    18            1073           1082             9
…                 …              …              …              …
8839                 60          125552         125582            30
8840                 60          125582         125612            30
8841                 60          125612         125642            30
8842                 60          125642         125672            30
8843               1799          125672         126575           903

      start_time_sec  stop_time_sec  duration_sec
0          14.277090      44.301717     30.024627
1          44.301717      44.602241      0.300524
2          44.602241      44.902563      0.300322
3          44.902563      45.202768      0.300204
4          45.202768      45.503007      0.300240
…                …              …           …
8839     4183.741890    4184.742721      1.000831
8840     4184.742721    4185.743529      1.000808
8841     4185.743529    4186.744364      1.000835
8842     4186.744364    4187.745223      1.000860
8843     4187.745223    4217.728557     29.983333

[8844 rows x 24 columns]
```

1.3.5 Stimulus objects

Once `sess.extract_info()`, each Session object now contains `Stim` objects.

These come in one of three subclasses: `Gabors`, `Visflow`, `Grayscr`, and can be accessed with: `sess.stims`, `sess.gabors`, `sess.visflow`, `sess.grayscr`.

The the `Stim` object `stim`, the Session object can be accessed with `stim.sess`.

[10]:
```
print(f"number of rois         : {sess.get_nrois()}")
print(f"mouse number           : {sess.mouse_n}")
print(f"mouse ID               : {sess.mouseid}")
print(f"gabor object           : {sess.gabors}")
print(f"2p frames per sec      : {sess.twop_fps:.2f}")
print(f"stimulus frames per sec: {sess.stim_fps:.2f}")
```

```
number of rois         : 628
mouse number           : 6
mouse ID               : 413663
gabor object           : Gabors (stimulus from session 764704289)
2p frames per sec      : 30.08
stimulus frames per sec: 59.95
```

1.4 2. Retrieving data of interest

1.4.1 Identifying stimulus segments of interest

From a `Session`'s `Stim`, you can get a list of segments that fit a specific criterion, e.g. **U segments** (unexpected, 3rd Gabor frame).

[11]:
```
gab_seg_ns = sess.gabors.get_segs_by_criteria(gabk=16, gabfr=3, unexp=1,␣
↪by="seg")
```

1.4.2 Identifying frame numbers of interest, to index the data

Then, you can retrieve the exact frame numbers that match these segments.

Specifically, you can access: * `twop` frame numbers, which index the two-photon data and pupil data, and * `stim` frame numbers, which index the running data.

Note: When retrieving the frame numbers, specifying `ch_fl` (check flanks) ensures that only frame numbers whose flanks are within the recording are returned. In other words, any frame number too close to the start or end of the recording (based on `pre`/`post` values), will be dropped.

[12]:
```
pre = 1.0
post = 1.0
twop_fr_ns = sess.gabors.get_fr_by_seg(gab_seg_ns, start=True, ch_fl=[pre,␣
↪post], fr_type="twop")["start_frame_twop"]
stim_fr_ns = sess.gabors.get_fr_by_seg(gab_seg_ns, start=True, ch_fl=[pre,␣
↪post], fr_type="stim")["start_frame_stim"]
```

1.4.3 Retrieving the data of interest

You can now get the **ROI / running / pupil data** corresponding these reference frames and the specified `pre` / `post` periods (in sec).

[13]:
```
roi_data_df = sess.gabors.get_roi_data(twop_fr_ns, pre, post, scale=True)
run_data_df = sess.gabors.get_run_data(stim_fr_ns, pre, post, scale=True)
pup_data_df = sess.gabors.get_pup_diam_data(twop_fr_ns, pre, post, scale=True)
```

1.4.4 Retrieving data statistics of interest

You can also directly obtain statistics on the data of interest.

[14]:
```
roi_stats_df = sess.gabors.get_roi_stats_df(
    twop_fr_ns, pre, post, integ=True, stats="mean", error="sem", byroi=False
)
```

[15]:
```
roi_stats_df
```

[15]:
```
datatype              roi_traces
bad_rois_removed             yes
scaled                        no
```

```
baseline                              no
integrated                           yes
smoothing                             no
fluorescence                         dff
general ROIs sequences
stats    None stat_mean     0.026752
              error_SEM     0.000911
```

1.4.5 Using hierarchical dataframes

Data and statistics are returned in a hierarchical dataframe with **columns** and **indices**.

This has the advantage of allowing metadata to be stored in dummy columns, however extracting data from these dataframes can be tricky, syntaxically.

[16]:
```
roi_data_df
```

[16]:
```
datatype                           roi_traces
bad_rois_removed                          yes
scaled                                    yes
baseline                                   no
integrated                                 no
smoothing                                  no
fluorescence                              dff
ROIs sequences time_values
0    0         -1.000000    -0.009556
               -0.966102    -0.644810
               -0.932203    -0.214521
               -0.898305    -0.116127
               -0.864407    -0.318214
…                                …
643  95         0.864407     0.050568
                0.898305     0.445153
                0.932203     0.108850
                0.966102     0.116475
                1.000000     0.213779

[3617280 rows x 1 columns]
```

To **extract a numpy array** with the correct dimensions from a hierarchical dataframe, you can use the following utility function: `gen_util.reshape_df_data()`.

Here, each index level, then column level is turned into a new axis, **i.e. ROIs x sequences x time_values** (In this case, `squeeze_cols` is set to True to prevent each dummy column from becoming its own axis.)

[17]:
```
roi_data = gen_util.reshape_df_data(roi_data_df, squeeze_cols=True)
print("ROI data shape: {} ROIs x {} sequences x {} time values".
 ↪format(*roi_data.shape))
```

```
ROI data shape: 628 ROIs x 96 sequences x 60 time values
```

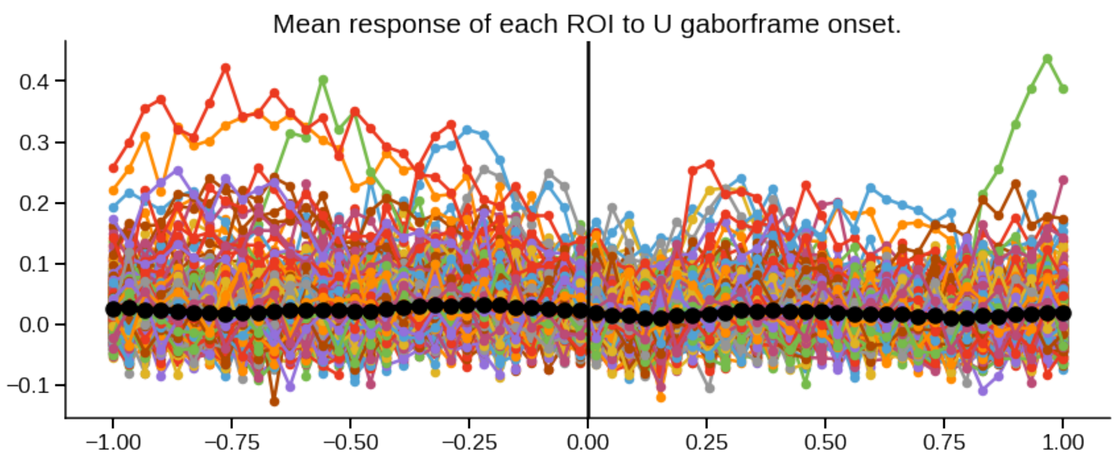
You can also retrieve the time stamps for each frame.

[18]:
```python
xran = roi_data_df.index.unique("time_values")
```

1.4.6 Visualizing the data

Finally, we can plot each ROIs mean activity across sequences, as well as a mean across ROIs.

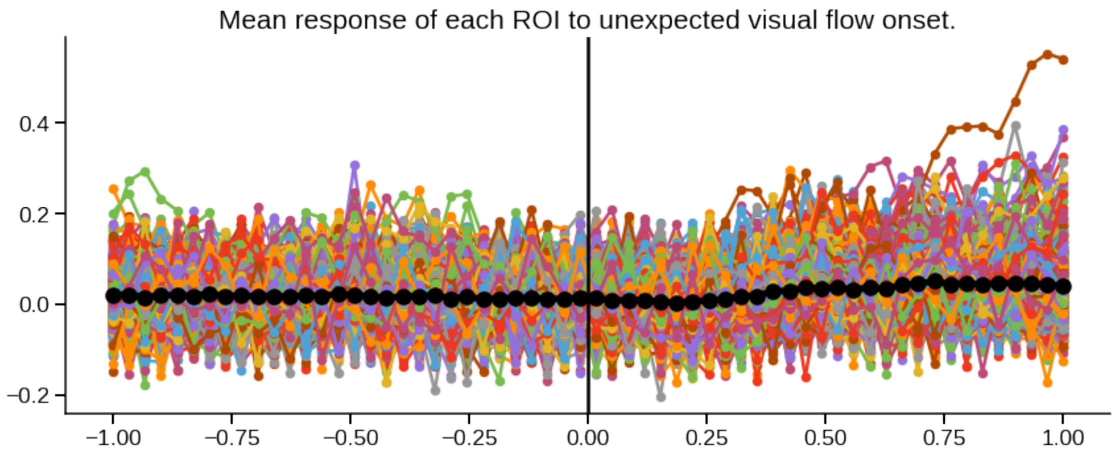
[19]:
```python
fig, ax = plt.subplots(1, figsize=(12, 5))
_ = ax.plot(xran, np.mean(roi_data, axis=1).T, marker=".") # mean per ROI
_ = ax.plot(xran, np.mean(np.mean(roi_data, axis=1).T, axis=1),
            lw=5, c="k", marker="o") # mean across ROIs
_ = ax.axvline(0, c="k")
_ = ax.set_title("Mean response of each ROI to U gaborframe onset.")
```



1.4.7 The same steps apply for Visflow

[20]:
```python
visflow_seg_ns = sess.visflow.get_segs_by_criteria(visflow_size=128, unexp=1,␣
 ↪remconsec=True, by="seg")

pre = 1.0
post = 1.0
twop_fr_ns = sess.visflow.get_fr_by_seg(
    visflow_seg_ns, start=True, ch_fl=[pre, post],␣
 ↪fr_type="twop")["start_frame_twop"]
stim_fr_ns = sess.visflow.get_fr_by_seg(
    visflow_seg_ns, start=True, ch_fl=[pre, post],␣
 ↪fr_type="stim")["start_frame_stim"]

roi_data_df = sess.visflow.get_roi_data(twop_fr_ns, pre, post, scale=True)
```

```
roi_data = gen_util.reshape_df_data(roi_data_df, squeeze_cols=True)
xran = roi_data_df.index.unique("time_values")

fig, ax = plt.subplots(1, figsize=(12, 5))
_ = ax.plot(xran, np.mean(roi_data, axis=1).T, marker=".") # mean per ROI
_ = ax.plot(xran, np.mean(np.mean(roi_data, axis=1).T, axis=1),
            lw=5, c="k", marker="o") # mean across ROIs
_ = ax.axvline(0, c="k")
_ = ax.set_title("Mean response of each ROI to unexpected visual flow onset.")
```



1.5 3. Tracked ROIs

ROI tracking was performed on the `production` data.
At any point, it is possible to **restrict the data returned** to only the tracked ROIs, called `sess.set_only_tracked_rois(True)`.

[21]:
```
sess.set_only_tracked_rois(True)
```

Here, we retrieve the data, **integrated over each sequence**.

[22]:
```
tracked_roi_data_df = sess.visflow.get_roi_data(twop_fr_ns, pre, post,␣
↪scale=True, integ=True)
```

The dataframe returned contains data only for tracked ROIs.

[23]:
```
tracked_roi_data_df
```

[23]:
```
datatype          roi_traces
bad_rois_removed         yes
scaled                   yes
baseline                  no
integrated               yes
```

```
smoothing                  no
fluorescence              dff
ROIs sequences
0    0               -0.077642
     1                0.002518
     2               -0.076000
     3                0.060652
     4               -0.000458
…                          …
242  28              -0.069519
     29               0.043961
     30               0.051469
     31              -0.011017
     32               0.188034

[4488 rows x 1 columns]
```

1.5.1 Extracting tracked ROI data correctly (!)

Importantly, the ROIs are now sorted in their tracking order, which ensures that they are correctly aligned across sessions.
As a result, the **"ROIs" index** may no longer be in increasing order, like in this example.

[24]:
```
roi_ns_ordered = tracked_roi_data_df.index.unique("ROIs").to_numpy()
print(f"ROI numbers, ordered for tracking:\n{', '.join([str(roi_n) for roi_n in␣
↪roi_ns_ordered])}")
```

```
ROI numbers, ordered for tracking:
0, 3, 5, 8, 9, 11, 23, 24, 32, 45, 49, 52, 53, 55, 64, 66, 67, 70, 75, 91, 111,
123, 155, 205, 213, 215, 218, 221, 222, 223, 225, 227, 228, 229, 230, 232, 234,
238, 240, 245, 246, 247, 251, 253, 254, 257, 264, 269, 270, 273, 294, 300, 308,
315, 336, 346, 347, 350, 371, 372, 373, 374, 376, 377, 378, 379, 381, 382, 383,
386, 389, 391, 392, 394, 398, 404, 406, 409, 413, 417, 428, 432, 434, 435, 446,
449, 453, 464, 482, 518, 523, 528, 529, 530, 531, 532, 533, 536, 538, 539, 540,
543, 547, 549, 552, 554, 555, 556, 557, 558, 562, 563, 565, 571, 572, 575, 579,
580, 582, 585, 596, 608, 625, 643, 63, 72, 85, 332, 405, 188, 129, 267, 486,
616, 1, 242
```

To **ensure that the tracked ROI order is preserved** when extracting the data, the safest option is to use the utility function introduced above, i.e. `gen_util.reshape_data_df()`. It will ensure that the order is preserved.

[25]:
```
tracked_roi_data = gen_util.reshape_df_data(tracked_roi_data_df,␣
↪squeeze_cols=True)
print("Tracked ROI data shape using the correct method, i.e., gen_util.
↪reshape_df_data()"
      "\n{} ROIs x {} sequences".format(*tracked_roi_data.shape))
```

```
Tracked ROI data shape using the correct method, i.e.,
gen_util.reshape_df_data()
136 ROIs x 33 sequences
```

Do not use the `.unstack()` method for hierarchical dataframes!

Even though the `.unstack()` method is typically a convenient way to extract a 2D array from a hierarchical dataframe, it will cause major problems here. Specifically, `.unstack()` internally triggers a resorting of the hierarchical indices. Thus, using it will completely mess up the tracked ROI order.

[26]:
```
tracked_roi_data_wrong = tracked_roi_data_df.unstack().to_numpy()
print("Tracked ROI data shape using the wrong method, i.e., .unstack()"
      "\n{} ROIs x {} sequences".format(*tracked_roi_data_wrong.shape))
```

```
Tracked ROI data shape using the wrong method, i.e., .unstack()
136 ROIs x 33 sequences
```

As you can see, the dimensions are still correct. However, the **ROI sorting is actually lost!**

For example, **ROI #8**, which should appear as index 3 in the array, is now at index 4.

[27]:
```
roi_idx_3_data = tracked_roi_data[3, :10]
print(f"Data for tracked ROI at index 3, when using the correct method: i.e.,␣
 ↪gen_util.reshape_df_data()"
      f"\n{', '.join([f'{val:.3f}' for val in roi_idx_3_data])} ...")
```

```
Data for tracked ROI at index 3, when using the correct method: i.e.,
gen_util.reshape_df_data()
0.032, -0.114, -0.035, -0.002, 0.032, -0.081, 0.004, -0.045, 0.046, 0.022 …
```

[28]:
```
roi_idx_3_data_wrong = tracked_roi_data_wrong[3, :10]
print(f"Data for tracked ROI at index 3, when using the wrong method: i.e., .
 ↪unstack()"
      f"\n{', '.join([f'{val:.3f}' for val in roi_idx_3_data_wrong])} ...")
```

```
Data for tracked ROI at index 3, when using the wrong method: i.e., .unstack()
-0.009, 0.013, 0.049, 0.026, -0.013, 0.741, -0.074, 0.004, 0.003, -0.035 …
```

[29]:
```
roi_idx_4_data_wrong = tracked_roi_data_wrong[4, :10]
print(f"Data for tracked ROI that should be at index 3 is instead at index 4,\n"
      "when using the wrong method: i.e., .unstack()"
      f"\n{', '.join([f'{val:.3f}' for val in roi_idx_4_data_wrong])} ...")
```

```
Data for tracked ROI that should be at index 3 is instead at index 4,
when using the wrong method: i.e., .unstack()
0.032, -0.114, -0.035, -0.002, 0.032, -0.081, 0.004, -0.045, 0.046, 0.022 …
```

1.5.2 Reset the session to start using all ROIs, again

[30]:
```
sess.set_only_tracked_rois(False)
```

1.6 4. Additional tips on indexing a hierarchical dataframe

[31]:
```
# getting columns
roi_data_series = roi_data_df["roi_traces"]

# getting specific ROIs, from their IDs, e.g. (0, 3, 4)
roi_data_specific_rois = roi_data_df.loc[([0, 3, 4])]

# getting specific sequences (0, 3, 4) for all ROIs <- second order index, so␣
↪requires a pandas slice
roi_data_specific_seqs = roi_data_df.loc[(pd.IndexSlice[:, [1, 20, 21]]), ]

# using both index and columns
roi_data_specific = roi_data_df.loc[(pd.IndexSlice[[0, 3, 4], [1, 20, 21],␣
↪-1]), ("roi_traces", "yes")]
roi_data_specific
```

[31]:
```
scaled                               yes
baseline                              no
integrated                            no
smoothing                             no
fluorescence                         dff
ROIs sequences time_values
0    1         -1.0            -0.114423
     20        -1.0            -0.502503
     21        -1.0            -0.020213
3    1         -1.0             0.647332
     20        -1.0             0.039799
     21        -1.0             0.066638
4    1         -1.0             0.339988
     20        -1.0             0.644120
     21        -1.0            -0.572354
```

1.7 5. Retrieving several Session objects, based on criteria

1.7.1 Identifying mice or session IDs to omit (pilot data only)

`sess_gen_util.all_omit()` allows keeping track of **which session IDs or mice must be left out**.

This actually **only applies to `pilot` data**, where some mice did not see all the stimuli of interst, and one session has incomplete data.
For the `prod` data, the lists are empty.

```
[32]: omit_sess, omit_mice = sess_gen_util.all_omit(runtype="prod")
```

1.7.2 Retrieving mouse / session numbers and IDs that fit specific criteria

`sess_gen_util.get_sess_vals()` can be used to retrieve information for sessions that meet certain criteria.
e.g., **session number 1, 2 or 3**, **production**, **dendritic plane**

```
[33]: mouse_ns, sess_ns, sessids = sess_gen_util.get_sess_vals(
          mouse_df, ["mouse_n", "sess_n", "sessid"], sess_n=[1, 2, 3],␣
       ↪runtype="prod", plane="dend", omit_sess=omit_sess,
          omit_mice=omit_mice, unique=False)
```

```
[34]: print("\n".join([f"mouse {m:2}: {sid} (session {n})" for m, sid, n in␣
       ↪zip(mouse_ns, sessids, sess_ns)]))
```

```
mouse  6: 764704289 (session 1)
mouse  6: 765193831 (session 2)
mouse  6: 766502238 (session 3)
mouse  8: 777914830 (session 1)
mouse  8: 778864809 (session 2)
mouse  8: 779650018 (session 3)
mouse  9: 826187862 (session 1)
mouse  9: 826773996 (session 2)
mouse  9: 827833392 (session 3)
mouse 10: 826338612 (session 1)
mouse 10: 826819032 (session 2)
mouse 10: 828816509 (session 3)
mouse 11: 823453391 (session 1)
mouse 11: 824434038 (session 2)
mouse 11: 825180479 (session 3)
```

1.7.3 Loading the sessions

`sess_gen_util.init_sessions()` can be used to **initialize the sessions** and **extract the requested data**.

```
[35]: dend_sessions = sess_gen_util.init_sessions(
          sessids[:5], datadir, mouse_df, full_table=False, omit=True, runtype="prod",
          roi=True, run=True
      )

      soma_sessions = sess_gen_util.init_sessions(
          [758519303], datadir, mouse_df, full_table=False, omit=True, runtype="prod",
          roi=True, run=True
      )
```

```
Creating session 764704289…
Loading stimulus and alignment info…
Loading ROI trace info…
Loading running info…
    WARNING: Session 764704289: 211 dropped running frames (~0.1%) (in pre-
processing).
Finished creating session 764704289.

Creating session 765193831…
Loading stimulus and alignment info…
Loading ROI trace info…
Loading running info…
    WARNING: Session 765193831: 345 dropped running frames (~0.1%) (in pre-
processing).
Finished creating session 765193831.

Creating session 766502238…
Loading stimulus and alignment info…
Loading ROI trace info…
Loading running info…
    WARNING: Session 766502238: 387 dropped running frames (~0.2%) (in pre-
processing).
Finished creating session 766502238.

Creating session 777914830…
Loading stimulus and alignment info…
Loading ROI trace info…
Loading running info…
    WARNING: Session 777914830: 381 dropped running frames (~0.2%) (in pre-
processing).
Finished creating session 777914830.

Creating session 778864809…
Loading stimulus and alignment info…
Loading ROI trace info…
Loading running info…
    WARNING: Session 778864809: 630 dropped running frames (~0.3%) (in pre-
processing).
Finished creating session 778864809.

Creating session 758519303…
Loading stimulus and alignment info…
Loading ROI trace info…
Loading running info…
    WARNING: Session 758519303: 175 dropped running frames (~0.1%) (in pre-
processing).
Finished creating session 758519303.
```

1.7.4 Using the loaded sessions

Now, one can run through the sessions, and run whatever analysis is needed.

Note here that, when calling `stim.get_segs_by_criteria()`, **features that do not apply to the stimulus** (e.g., `gabfr` for the `visflow` stimulus) **are simply ignored**.

[36]:
```
for sess in dend_sessions + soma_sessions:
    print(f"Session ID: {sess.sessid} (mouse {sess.mouse_n}, session {sess.
 ↪sess_n})")
    for stimtype in ["visflow", "gabors"]:
        stim = sess.get_stim(stimtype)
        segs = stim.get_segs_by_criteria(
            visflow_size=128, unexp=1, gabk=16, gabfr=3, by="seg",
            remconsec=(stimtype == "visflow")
            )
        print(f"    {stimtype}: {len(segs)} sequences")
```

```
Session ID: 764704289 (mouse 6, session 1)
    visflow: 33 sequences
    gabors: 96 sequences
Session ID: 765193831 (mouse 6, session 2)
    visflow: 34 sequences
    gabors: 98 sequences
Session ID: 766502238 (mouse 6, session 3)
    visflow: 29 sequences
    gabors: 94 sequences
Session ID: 777914830 (mouse 8, session 1)
    visflow: 32 sequences
    gabors: 83 sequences
Session ID: 778864809 (mouse 8, session 2)
    visflow: 29 sequences
    gabors: 88 sequences
Session ID: 758519303 (mouse 1, session 1)
    visflow: 31 sequences
    gabors: 94 sequences
```

1.8 6. Retrieving ROI masks from session.

Boolean ROI masks can be obtained for each Session.

1.8.1 Dendritic mask types

For **dendritic sessions**, the Session is built to assume that `extr` (not `allen`) ROI data is to be used. This can be checked by checking `self.dend`. As long as `self.dend` is properly set, the correct ROI data and masks will be loaded.

The `allen` masks were extracted with a pipeline tailored to somatic ROIs, and are therefore not preferred for dendritic data.

In contrast, the `extr` masks were extracted with the EXTRACT pipeline, which specifically enables dendrite-shaped ROIs to be identified.

Note that, for this reason, ***only the extr dendritic ROIs and masks*** are included in the data in NWB formatted data.

[37]:
```
dend_sess = dend_sessions[0]
print(f"Dendritic session, ROI type: {dend_sess.dend}")

soma_sess = soma_sessions[0]
print(f"Somatic session, ROI type: {soma_sess.dend}")
```

```
Dendritic session, ROI type: extr
Somatic session, ROI type: allen
```

1.8.2 Loading masks

Masks can be loaded as follows, with dimensions: **ROI x height x width**, retrieving only masks for ROIs that are valid (when evaluated by their dF/F traces).

Note that **if sessions are set to use only tracked ROIs**, as described above, only masks for the tracked ROIs (sorted in the tracking order) will be returned.

[38]:
```
dend_mask = dend_sess.get_roi_masks()
soma_mask = soma_sess.get_roi_masks()
```

In most functions, by default, ROIs that are considered **bad (non valid)** are automatically removed (`rem_bad=True`).
Note that, **for the NWB data**, the ***bad ROIs were removed altogether***.

These ROIs either:
(1) contain NaN/Infs values or
(2) have been deemed too noisy.

If, for whatever reason, **all masks are needed**, including those for the bad ROIs,
(1) ensure that the session is currently set to return all ROI data, with `sess.only_tracked_rois(False)`, then
(2) call `self.get_roi_masks(rem_bad=False)`.

Of course, as explained above, if using the NWB data, there are no bad ROIs.

[39]:
```
dend_sess.set_only_tracked_rois(False)
soma_sess.set_only_tracked_rois(False)

dend_mask_all = dend_sess.get_roi_masks(rem_bad=False)
soma_mask_all = soma_sess.get_roi_masks(rem_bad=False)
```

1.8.3 Bad ROIs

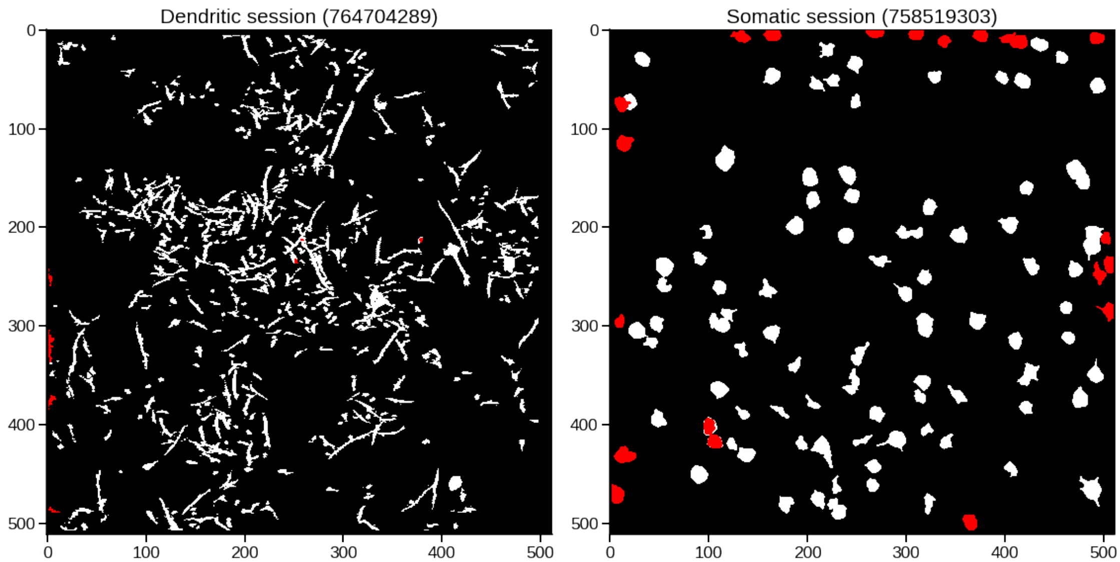
When using the data in its original format, one can get a list of bad ROIs, by using `self.get_bad_rois()`

[40]:
```
dend_nan_masks = np.asarray(dend_sess.get_bad_rois(fluor="dff"))
soma_nan_masks = np.asarray(soma_sess.get_bad_rois(fluor="dff"))

dend_valid = np.ones(len(dend_mask_all))
dend_valid[dend_nan_masks] = 0

soma_valid = np.ones(len(soma_mask_all))
soma_valid[soma_nan_masks] = 0
```

1.8.4 Visualizing ROI masks

`sess_plot_util.plot_ROIs()` can be used to visualize ROIs, where specific ROIs can be set to red using a `valid_mask`.

[41]:
```
fig, ax = plt.subplots(1, 2, figsize=(16, 9))
sess_plot_util.plot_ROIs(ax[0], dend_mask_all, valid_mask=dend_valid)
_ = ax[0].set_title(f"Dendritic session ({dend_sess.sessid})")

sess_plot_util.plot_ROIs(ax[1], soma_mask_all, valid_mask=soma_valid)
_ = ax[1].set_title(f"Somatic session ({soma_sess.sessid})")
```

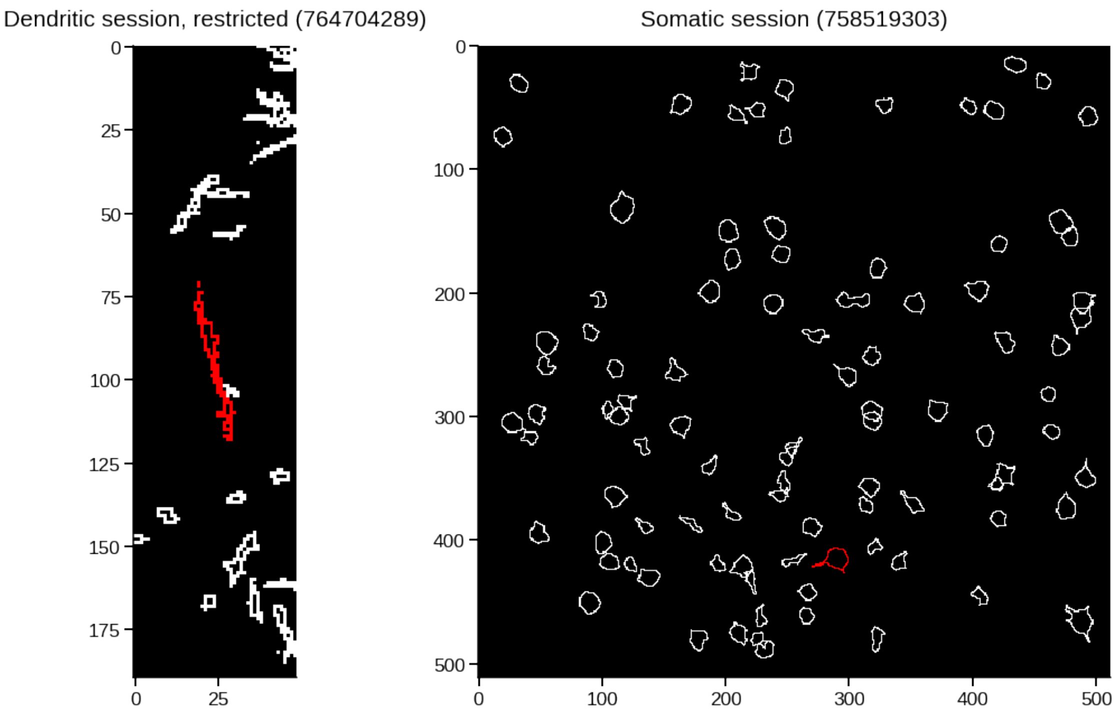


1.8.5 Visualizing ROI mask contours

`sess_plot_util.plot_ROI_contours()` can be used to visualize ROI contours, optionally restricted to around an ROI of interest.

[42]:
```
fig, ax = plt.subplots(1, 2, figsize=(16, 9))
sess_plot_util.plot_ROI_contours(ax[0], dend_mask, outlier=490, restrict=True)
```

```
_ = ax[0].set_title(f"Dendritic session, restricted ({dend_sess.sessid})", y=1.
↪02)

sess_plot_util.plot_ROI_contours(ax[1], soma_mask, outlier=30)
_ = ax[1].set_title(f"Somatic session ({soma_sess.sessid})", y=1.02)
```



1.9 7. Last notes

There is much more to the codebase, and even to the `Session` and `Stim` objects, and almost all functions and methods are thoroughly documented.

When looking to implement a new analysis, consider checking to see whether relevant functions have already been implemented in:
* `analysis/session.py`
* `analysis/basic_analys.py`
* `sess_util/sess_gen_util.py`

1.9.1 Methods/properties attached to Session and Stim objects.

[43]:
```
print(f"{sess}{gen_util.create_attribute_str(sess)}")
```

```
Session (758519303)

  Public properties:
    self.align_pkl
```

```
self.all_files
self.any_files
self.behav_video_h5
self.correct_data_h5
self.date
self.dend
self.depth
self.dir
self.drop_tol
self.expdir
self.expid
self.gabors
self.grayscr
self.home
self.line
self.max_proj
self.max_proj_png
self.mouse_df
self.mouse_dir
self.mouse_n
self.mouseid
self.n_stims
self.notes
self.nwb
self.only_tracked_rois
self.pass_fail
self.plane
self.procdir
self.pup_data_h5
self.pup_video_h5
self.roi_extract_json
self.roi_facts_df
self.roi_mask_file
self.roi_masks
self.roi_names
self.roi_objectlist
self.roi_trace_dff_h5
self.roi_trace_h5
self.run_data
self.runtype
self.segid
self.sess_n
self.sessid
self.stim2twopfr
self.stim_df
self.stim_fps
self.stim_pkl
self.stim_seed
```

```
    self.stim_sync_h5
    self.stims
    self.stimtypes
    self.time_sync_h5
    self.tot_stim_fr
    self.tot_twop_fr
    self.tracked_rois
    self.twop2stimfr
    self.twop_fps
    self.visflow
    self.zstack_h5

  Public methods:
    self.check_flanks()
    self.convert_frames()
    self.data_loaded()
    self.extract_info()
    self.get_active_rois()
    self.get_bad_rois()
    self.get_fr_ran()
    self.get_frames_timestamps()
    self.get_nrois()
    self.get_plateau_roi_traces()
    self.get_pup_data()
    self.get_roi_masks()
    self.get_roi_seqs()
    self.get_roi_trace_path()
    self.get_roi_traces()
    self.get_run_velocity()
    self.get_run_velocity_by_fr()
    self.get_single_roi_trace()
    self.get_stim()
    self.load_pup_data()
    self.load_roi_info()
    self.load_run_data()
    self.set_only_tracked_rois()
```

[44]:
```
print(f"{sess.gabors}{gen_util.create_attribute_str(sess.gabors)}")
```

```
Gabors (stimulus from session 758519303)

  Public properties:
    self.all_gabfr
    self.all_gabfr_mean_oris
    self.block_params
    self.deg_per_pix
    self.exp_gabfr
    self.exp_gabfr_mean_oris
```

```
    self.exp_max_s
    self.exp_min_s
    self.kappas
    self.n_patches
    self.n_segs_per_seq
    self.ori_ran
    self.phase
    self.seg_len_s
    self.sess
    self.sf
    self.size_ran
    self.stim_fps
    self.stim_params
    self.stimtype
    self.unexp_gabfr
    self.unexp_gabfr_mean_oris
    self.unexp_max_s
    self.unexp_min_s
    self.win_size

  Public methods:
    self.get_A_frame_1s()
    self.get_A_segs()
    self.get_all_unexp_segs()
    self.get_all_unexp_stim_fr()
    self.get_fr_by_seg()
    self.get_frames_by_criteria()
    self.get_n_fr_by_seg()
    self.get_pup_diam_data()
    self.get_pup_diam_stats_df()
    self.get_roi_data()
    self.get_roi_stats_df()
    self.get_run()
    self.get_run_data()
    self.get_run_stats_df()
    self.get_segs_by_criteria()
    self.get_segs_by_frame()
    self.get_start_unexp_segs()
    self.get_start_unexp_stim_fr_trans()
    self.get_stats_df()
    self.get_stim_beh_sub_df()
    self.get_stim_df_by_criteria()
    self.get_stim_par_by_frame()
    self.get_stim_par_by_seg()
```

[45]:
```
print(f"{sess.visflow}{gen_util.create_attribute_str(sess.visflow)}")
```

```
Visflow (stimulus from session 758519303)
```

```
  Public properties:
    self.block_params
    self.deg_per_pix
    self.exp_max_s
    self.exp_min_s
    self.main_flow_direcs
    self.n_squares
    self.prop_flipped
    self.seg_len_s
    self.sess
    self.speed
    self.square_sizes
    self.stim_fps
    self.stim_params
    self.stimtype
    self.unexp_max_s
    self.unexp_min_s
    self.win_size

  Public methods:
    self.get_all_unexp_segs()
    self.get_all_unexp_stim_fr()
    self.get_dir_segs_exp()
    self.get_fr_by_seg()
    self.get_frames_by_criteria()
    self.get_n_fr_by_seg()
    self.get_pup_diam_data()
    self.get_pup_diam_stats_df()
    self.get_roi_data()
    self.get_roi_stats_df()
    self.get_run()
    self.get_run_data()
    self.get_run_stats_df()
    self.get_segs_by_criteria()
    self.get_segs_by_frame()
    self.get_start_unexp_segs()
    self.get_start_unexp_stim_fr_trans()
    self.get_stats_df()
    self.get_stim_beh_sub_df()
    self.get_stim_df_by_criteria()
```

[46]:
```
print(f"{sess.grayscr}{gen_util.create_attribute_str(sess.grayscr)}")
```

```
Grayscr (session 758519303)

  Public properties:
    self.sess
```

```
  Public methods:
    self.get_all_fr()
    self.get_start_fr()
    self.get_stop_fr()
```

1.9.2 Example Session and Stim object property values.

Properties with long values (e.g., long dataframes, arrays, lists, strings) are omitted, for brevity.

```
[47]: print(f"{sess}{gen_util.create_property_str(sess, max_length=40)}")
```

```
Session (758519303)

  Public property values:
    self.all_files: True
    self.any_files: True
    self.date: 20180926
    self.dend: allen
    self.depth: 175
    self.drop_tol: 0.0003
    self.expid: 759038671
    self.gabors: Gabors (stimulus from session 758519303)
    self.grayscr: Grayscr (session 758519303)
    self.home: ../../data/OSCA
    self.line: L23-Cux2
    self.mouse_dir: True
    self.mouse_n: 1
    self.mouseid: 408021
    self.n_stims: 2
    self.notes: nan
    self.nwb: False
    self.only_tracked_rois: False
    self.pass_fail: P
    self.plane: soma
    self.roi_mask_file: None
    self.runtype: prod
    self.segid: 759205610
    self.sess_n: 1
    self.sessid: 758519303
    self.stim_fps: 59.95049782968851
    self.stim_seed: 30587
    self.stimtypes: ['gabors', 'visflow']
    self.tot_stim_fr: 251999
    self.tot_twop_fr: 126741
    self.twop2stimfr: [nan nan nan … nan nan nan]
    self.twop_fps: 30.078378454283577
```

[48]:
```
print(f"{sess.gabors}{gen_util.create_property_str(sess.gabors,␣
↪max_length=40)}")
```

```
Gabors (stimulus from session 758519303)

  Public property values:
    self.all_gabfr: ['A', 'B', 'C', 'D', 'G', 'U']
    self.all_gabfr_mean_oris: [0.0, 45.0, 90.0, 135.0, 180.0, 225.0]
    self.deg_per_pix: 0.06251912565744862
    self.exp_gabfr: ['A', 'B', 'C', 'D', 'G']
    self.exp_gabfr_mean_oris: [0.0, 45.0, 90.0, 135.0]
    self.exp_max_s: 90
    self.exp_min_s: 30
    self.kappas: [16]
    self.n_patches: 30
    self.n_segs_per_seq: 5
    self.ori_ran: [0, 360]
    self.phase: 0.25
    self.seg_len_s: 0.3
    self.sess: Session (758519303)
    self.sf: 0.04
    self.size_ran: [204, 408]
    self.stim_fps: 59.95049782968851
    self.stim_params: ['gabor_kappa']
    self.stimtype: gabors
    self.unexp_gabfr: ['U']
    self.unexp_gabfr_mean_oris: [90.0, 135.0, 180.0, 225.0]
    self.unexp_max_s: 6
    self.unexp_min_s: 3
    self.win_size: [1920, 1200]
```

[49]:
```
print(f"{sess.visflow}{gen_util.create_property_str(sess.visflow,␣
↪max_length=40)}")
```

```
Visflow (stimulus from session 758519303)

  Public property values:
    self.deg_per_pix: 0.06251912565744862
    self.exp_max_s: 90
    self.exp_min_s: 30
    self.main_flow_direcs: ['left (nasal)', 'right (temp)']
    self.n_squares: [105]
    self.prop_flipped: 0.25
    self.seg_len_s: 1
    self.sess: Session (758519303)
    self.speed: 799.7552664756905
    self.square_sizes: [128]
    self.stim_fps: 59.95049782968851
```

```
    self.stimtype: visflow
    self.unexp_max_s: 4
    self.unexp_min_s: 2
    self.win_size: [1920, 1200]
```

[50]:
```
print(f"{sess.grayscr}{gen_util.create_property_str(sess.grayscr,␣
 ↪max_length=40)}")
```

```
Grayscr (session 758519303)

  Public property values:
    self.sess: Session (758519303)
```

[ ]:
```
```